A DATA-INTEGRATED SIMULATION-BASED OPTIMIZATION APPROACH FOR NURSE-PATIENT ASSIGNMENT

by

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To my Mother, Father, and Sister.

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ABSTRACT

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This research develops a novel data-integrated simulation to evaluate nurse-patient assignments (SIMNA) based on a real data set provided by Baylor Regional Medical Center (Baylor) in Grapevine, Texas. Tree-based models and kernel density estimation were utilized to extract important knowledge from the data for the simulation. Classification and Regression Tree models, data mining tools for prediction and classification, were used to develop five tree structures: (*a*) four classification trees, from which transition probabilities for nurse movements are determined; and (*b*) a regression tree, from which the amount of time a nurse spends in a location is predicted based on factors such as the primary diagnosis of a patient and the type of nurse. Kernel density estimation is used to estimate the continuous distribution for the amount of time a nurse spends in a location. Results obtained from SIMNA to evaluate nurse-patient assignments in medical/surgical unit I of Baylor are discussed. With the aid of SIMNA, in addition to evaluating assignments at the beginning of a shift, two policies named OPT and HEU are introduced to make nurse-patient assignments for patient admits during a

shift. Results from fifty problems created with different initial assignments to evaluate the policies are presented.

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CHAPTER 1

INTRODUCTION

1.1 Nurse Shortage

The health care system in the United States has a shortage of nurses. In 2000, according to the U.S. Department of Health and Human Services (DHHS), the national shortage for registered nurses was 110,000 or 6%. DHHS anticipates that the shortage will grow relatively slowly until it reaches 12% around 2010. From then, it is expected to worsen at a faster rate and reach a 20% shortage by 2015. A shortage of 3% or more was observed in 30 states during 2000, and similar shortages are predicted to occur in 44 states by 2020 [42]. These statistics show that the severity of this shortage is widespread. On the other hand, the need for health care keeps increasing due to aging baby boomers [1] and elderly patients [2]. As a consequence of the nurse shortage, it is natural to expect issues such as job burnout and poor patient care [5]. Considering this severe shortage, a careful planning of nurse resources is needed. Nurse planning typically has four stages; *nurse budgeting, nurse scheduling, nurse rescheduling* and *nurse assignment*. Among these stages, nurse assignment is a crucial stage in which a charge nurse assigns each nurse to a set of patients. In an attempt to ease the health care system from the burden of the nurse shortage and standardize nurse workload, California has set a limit on the number of patients that can be assigned to nurses at the same time [20]. Such restrictions may reduce nurses' workload, but will unlikely resolve the issue because differences in workload among nurses depend on the set of patients to which a nurse is assigned. Thus, in addition to limiting the number of patients per nurse, it is important to optimize the nurse-patient assignments for a balanced workload. In the literature, most of the relevant research focuses only on solving issues in nurse budgeting, nurse rostering and nurse scheduling methodologies [3, 19, 44, 50, 58, 84, 9, 7, 11, 38]. By contrast, our research develops a data-integrated simulation to evaluate nurse-patient assignments (SIMNA) that utilizes patterns in real a data set provided by Baylor Regional Medical Center to balance workload.

1.2 Simulation States

In traditional stochastic simulation models, transition probabilities are obtained either subjectively or by looking at all possible combinations of the levels of the simulation state variables. If the system under consideration is complex, such as nurse movement, then a subjective approach is unlikely to be accurate, and an approach using all possible combinations of the states will be impractical. In the past, in order to reduce the number of simulation variables, factorial designs and screening methods were used [16, 26, 67]. Even after eliminating some of the variables, a few remaining variables could lead to a huge number of combinations for the simulation. For instance, six categorical variables with ten categories each will lead to a million possible states in the simulation. Obtaining accurate transition probabilities for such a huge simulation model is still difficult. In this research, using data from Baylor Regional Medical Center (Baylor) in Grapevine, Texas, we present a new methodology to reduce the number of combinations and find transition probabilities for stochastic simulation models. Tree-based models and kernel density estimates were utilized to extract important knowledge about the workload of nurses from an encrypted data set provided by Baylor for four care units. The four units include two medical/surgical units, one mom/baby unit, and one high-risk labor-and-delivery unit. Classification and Regression Trees [17], a data mining tool for prediction and classification, was applied to the Baylor data to develop five tree structures: (a) four classification trees, from which transition probabilities for nurse movements are determined; and (b) a regression tree, from which the amount of time a nurse spends in a location is predicted based on factors such as the primary diagnosis of a patient and the type of nurse. From a methodological perspective, the core of this research was building an efficient simulation that includes embedded Classification and Regression Trees (CART) to determine transitions of the simulation state. It statistically reduces the simulation state space. To the best of our knowledge, utilizing tree-based models to extract the logic of the system, reduce the complexity of the system, and ultimately drive a simulation has not previously been published. Simulation models developed with this approach will be much more representative of actual systems and more efficient than those that consider all possible combinations.

Following are three major contributions made in this dissertation:

- This research introduces a novel approach, discussed in chapter 3, to the simulation community for constructing efficient simulation models based on data mining. This way of simulation modeling avoids misrepresentation of system dynamics and characteristics because it is entirely based on the pattern learned from a real data set collected from the system over a long period of time. Moreover, this approach reduces simulation states and is consequently more efficient to run.
- This research introduces a tool, discussed in chapter 4, to evaluate nurse-to-patient assignments and enable decisions in real time. At Baylor, prior to a shift, the decision to hire agency nurses is determined by nurse supervisors, who assess whether the set of scheduled nurses is sufficient for that shift. The SIMNA model can aid them in their decisions by providing a tool to test nurse-to-patient assignments.
- This research introduces an efficient policy, discussed in chapter 5, to obtain nurse-patient assignments of new admits during a shift. Traditionally, a nurse who has the least number of patients or who had the least workload until the instance of arrival would get the newly-admitted patient. This approach could worsen the imbalance as future workload is totally ignored. The new policy which considers the past as well as the expected future and is likely to reduce the imbalance.

The rest of this dissertation is organized as follows: In Chapter 2, a literature review on nursing research and the contributions of this research are given. A brief introduction on data and notation, tree structures used to build the simulation model, kernel density estimation, and the simulation structure are given in Chapter 3. Chapter 4 presents four different assignment policies and test results from SIMNA for a set of nurse-patient assignments prior to a shift in medical/surgical unit I. Chapter 5 introduces an efficient policy to assign a newly-admitted patient during a given shift. In Chapter 6, a discussion on six possible areas for future work is provided.

CHAPTER 2

LITERATURE REVIEW AND CONTRIBUTION

2.1 Literature Review

There are three major components in this research, i.e, nurse planning, data mining, and simulation modeling. This chapter gives a brief literature review on each of these topics.

2.1.1 Nurse Planning

Nurse planning typically has four stages: nurse budgeting, nurse scheduling, nurse rescheduling, and nurse assignment. In the literature, most of the relevant research focuses on the first three stages of planning.

In nurse budgeting: Kao and Queyranne [48] showed that a single-period demand estimate gives a good approximation for nurse budgeting cost. Trivedi [77] used mixed-integer goal programming to optimize the expenses for nurse personnel. Kao and Tung [49] used a linear programming-based approach to assess needs for regular, overtime, and agency workforce levels for a given time period.

In nurse scheduling: Warner and Prawda [85] optimized nurse schedules by formulating a mixed-integer quadratic programming problem. Later, Warner [84] formulated and solved another multiple-choice math programming scheduling problem incorporating nursing preferences. Miller et al. [58] minimized an objective function that balanced the trade-off between staffing coverage and preferences of nurses. Burke, Cowling and Caumaecker [19] and Burke, Caumaecker and Petrovic [18] used a combination of tabu search, genetic algorithm, and steepest descent improvement heuristics to solve a nurse rostering problem. Aickelin and Paul [4] formulated the nurse scheduling as an integer programming problem and compared solutions from different algorithms using statistical techniques. Azaiez and Sharif [7] computerized the nurse-scheduling problem for Riyadh Al-Kharj hospital (in Saudi Arabia) using a 0-1 goal programming that incorporated nurses' preferences and hospital objectives. Wong and Chan [87] introduced a probability-based ordering method for a nurse rostering problem that considered twelve nurses. It reported its solution time as half a second. Beddoe and Petrovic [11] used genetic algorithm to solve another nurse rostering problem by considering violations made in prior rosters. Gutjahr and Rauner [38] used ant colony optimization to schedule nurses for four weeks among different hospitals in a region.

In nurse rescheduling: Benton [13] showed how the scheduled nursing scenario changes when the patient acuity and number of patients change. Walts and Kapadia [83] developed a patient classification system to redistribute nursing personnel across different care units based on patient acuity. Bard [10, 9] formulated a nurse rescheduling integer programming problem and solved it using branch and price considering the resource shortage, demand drop, and nurse preferences. CDHS [20] required health care providers to maintain certain nurse-to-patient ratios for improving quality of care. Vericourt and Jennings [81], using a queuing approach, showed that same set of ratios for different sizes of care units lead to inconsistent amounts of care. Alternatively, they proposed a heuristic-based policy to provide better care. However, their model allowed nurses to serve unassigned patients, which is discouraged in practice for maintaining continuity of care.

In nurse assignment: Mullinax and Lawley [59] formulated and solved an integer programming problem using heuristics to assign nurses to patients by balancing workload for nurses based on patient acuity in a neonatal intensive care. Punnakitikashem et al. [62] formulated and solved a two-stage stochastic integer programming nurse assignment problem to minimize excess workload of nurses. None of the methods discussed above provides a tool to evaluate nurse-patient assignments to make decisions in real time. Also, other methods did not use real data to reflect the real system as extensively as the approach presented in this dissertation.

2.1.2 Data Mining

Data Mining can be broadly classified into two groups: supervised learning and unsupervised learning. In supervised learning, an outcome variable is present to guide the learning process. Whereas, in unsupervised learning or clustering, one wants to observe only the features and have no measurements of the outcome. Data Mining can be viewed as statistical learning from data or more generally as an approach that seeks to uncover patterns in data. Typically, learning could be an outcome measurement, quantitative (like the amount of time spent by nurses in a given location) or categorical (like different locations a nurse visits), that one wants to predict based on set of features (like type of the nurse, diagnosis of the patient, and time of the day) if available [40]. Supervised learning is the subject of interest in this dissertation as we deal with predicting the time spent and location for nurses. Regression, kernel methods, tree based models, neural networks, and support vector machines are some popular supervised learning methods. Regression methods are one of the traditional tools used for prediction [60, 40, 82]. Multivariate Adaptive Regression Splines (MARS), a spline based prediction model [33] was recently applied to different prediction problems [25, 78, 24, 70, 61]. Neural networks, a nonlinear statistical model [63, 41], often represented by a network diagram, can be used for prediction or classification. Le Cun et al. [55] applied neural networks to identify handwritten zip code digits. Cervellera, Chen, and Wen [21] and Cervellera, Wen, and Chen [23] approximated stochastic dynamic programming value functions of an inventory forecasting problem and a water reservoir problem with neural networks. Classification and Regression Trees [17], a data mining tool for prediction and classification, is used in this research for its applicability to regression and classification problems, and its readily usable tree structures in simulation.

2.1.3 Simulation Modeling in Health Care

Studying industrial systems using simulation was prevelant as early as the late 1950's and early 1960's. Youle et al. [88] and Clementson [27] discuss simulations of different industrial processes available at that time. In health care, simulation modeling has been used to study a wide range of problems. Bailey [8] and Kachhal et al. [47] studied patient queues and waiting times. Smith and Warner [73], Lim et al. [56], Hancock and Walter [39] studied patient admission and its impact. Zilm et al. [90] and Dumas [29, 30] modeled and analyzed patient bed planning and utilization under different scenarios. Kumar and Kapur [53], Draeger [28] and Evans et al. [32] evaluated nurse schedules for the emergency care department. In recent years, Zenios et al. [89], Kreke et al. [52], and Shechter et al. [66] utilized simulation models to study organ allocation systems. A comprehensive review of health care simulation models can be found in Klein et al. [51] and Jun et al. [46]. In the literature, most of the health care staffing simulations analyzed only emergency departments in hospitals. Moreover, all the simulation models in the literature, both deterministic and stochastic, were modeled based on the knowledge of experts. If the system under consideration is complex, such as nurse movement in hospitals, then it is impossible even for the experts to comprehend the intricacies of the system by observation. Whereas, the simulation modeling technique introduced in this research captures the system dynamics from a real data set collected from the system and requires only minimal input from the experts.

2.2 Contribution

There are three major contributions from this dissertation:

- This research introduces a novel approach to the simulation community for constructing efficient simulation models based on data mining. This way of simulation modeling avoids misrepresentation of system dynamics and characteristics because it is entirely based on the pattern learned from a real data set collected from the system over a long period of time. Moreover, this approach reduces simulation states and is consequently more efficient to run.

- This research introduces a tool to evaluate nurse-to-patient assignments and enable decisions in real time. At Baylor, prior to a shift, the decision to hire agency nurses is determined by nurse supervisors, who assess whether the set of scheduled nurses is sufficient for that shift. The SIMNA model can aid them in their decisions by providing a tool to test nurse-to-patient assignments.
- This research introduces an efficient policy to obtain nurse-patient assignments of new admits during a shift. Traditionally, a nurse who has the least number of patients or who had the least workload until the instance of arrival would get the newly-admitted patient. This approach could worsen the imbalance as future workload is totally ignored. The new policy considers the past as well as the expected future and is likely to reduce the imbalance.

CHAPTER 3

DATA-INTEGRATED SIMULATION

3.1 Data Description

At Baylor, each nurse wears a locating device that transmits data to a repository, where the data automatically expire after one month. Baylor provided data for this research from four care units: Medical/Surgical unit I, Medical/Surgical unit II, Mom/Baby unit, and High-Risk Labor unit. These *nurse data* contain information on month, day, shift, time, location, nurse, nurse type and time spent for the location visited by the nurse. Baylor also provided *patient data*, which contain information on admit date, discharge date, room number and diagnosis code for each patient. These two data sets were merged by matching the date and location information and are referred to as the *merged data*. The resulting *merged data* have all the variables from the nurse and patient data sets. To preserve the confidentiality of nurses, patients and the medical center, an encryption code using the U16807 method [54] was developed and employed to the data before our analysis. U16807 method was chosen for encryption because of its efficiency to handle cycling. An example for date and location variables in our data before and after encryption is shown in Table 3.1.

Table 3.1. Encryption Example

Variable	**Before**	**After**
Date	4/5/04	2/15/73622
Room	442	704

Two new variables were created to hold information on the previous two locations visited for each location entered by nurses to predict patterns in their movements. In a related research, presented in Sundaramoorthi, Chen, Rosenberger, Kim, and Behan [76] and Sundaramoorthi, Chen, Kim, Rosenberger and Behan [74], seven variables were created to hold information on previous seven locations. The simulation models developed with seven previous locations were found to overfit the pattern based on movements and hence insensitive to other practically important variables. For this reason, unlike Sundaramoorthi, Chen, Rosenberger, Kim, and Behan [76] and Sundaramoorthi, Chen, Kim, Rosenberger, and Behan [74], the simulation presented here includes location variables that specify only two previous locations and the current location to avoid overfitting patterns based purely on nurse movements. Furthermore, two new variables were created to indicate the acuity of patients and nurse-patient assignments. Four levels of acuity were considered depending upon the amount of care received by the patients. To create nurse-patient assignment variable, it is assumed that the nurse who spent the most time in a patient's room during a shift is the nurse assigned to that patient for that shift. After processing the data, medical/surgical unit I, medical/surgical unit II, mom/baby unit, and high-risk labor-and-delivery unit have about 570,660, 418,683, 315,997, and 210,457 observations, respectively. Following the conclusions in Sundaramoorthi et al. [75] and further similar analysis presented in Sundaramoorthi, Chen, Rosenberger, Kim, and Behan [76], the following types of variables with their specific levels are considered significant for the methodology presented here.

1. Location : patient rooms, nurse station, break room, reception desk, and medical room.
2. Nurse Type: registered nurse (RN), licensed vocational nurse (LVN), and nurse aide (NA).
3. Diagnosis Code : 19 categories covering the range of diagnosis codes, and 2 dummy categories for empty patient rooms and non-patient locations. See INGENIX [43] for more details on diagnosis codes.

4. Shift: 3 weekday shifts (8 hours each) and 2 weekend shifts (12 hours each).
5. Hour: 24 hour ranges covering a complete day.
6. Assignment: An assigned nurse entering a patient room (1), an unassigned nurse entering a patient room (0), and a nurse entering any location other than patient rooms (2).
7. Time Spent: Time Spent is the dependent variable that denotes the amount of time a nurse spends in a given location.

Data from different care units were handled separately as the number of categorical levels of the considered variables, listed above, differed slightly among different care units. In this dissertation, we maintain the following notations: X_S, X_T, X_{NT}, X_L, X_A, and X_D are the variables representing shift, hour, nurse type, current location, assignment, and primary diagnosis of the patient in a current location, respectively. N_S, N_T, N_{NT}, N_L, N_A, and N_D are the number of levels of X_S, X_T, X_{NT}, X_L, X_A, and X_D, respectively. X_{P1L}, and X_{P2L} are the variables representing the two previous locations with X_{P1L} being the latest and X_{P2L} being the oldest among the two locations visited before any current location. X_{P1L} and X_{P2L} have the same number of levels (N_L) as of X_L. For each nurse, $X_{AL1}, \ldots, X_{ALR}$ are the binary variables indicating patients assigned to her/him in a shift. R is the number of patient rooms in a care unit. $X_{DL1}, \ldots, X_{DLR}$ are the variables representing primary diagnosis of patients in rooms 1 to R.

3.2 Data Mining for Simulation

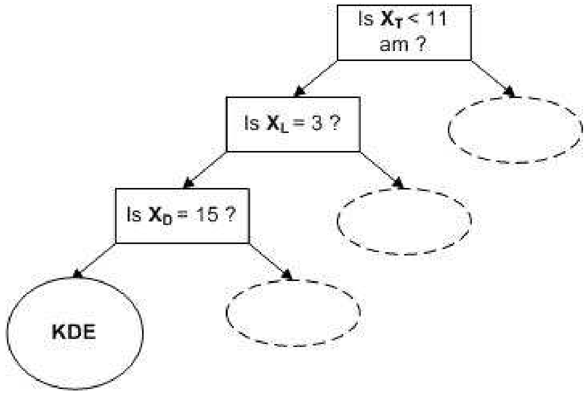
3.2.1 Classification and regression trees

Classification and Regression Trees (CART) are data mining tools for prediction and classification [17, 40]. CART utilizes recursive binary splitting to uncover structure in a high-dimensional space. CART, on application to a data set, will partition the input space into many disjoint sets, where values within a set have a more similar response measure than values in different sets. Salford Systems' CART® software (www.salfordsystems.com) was used to obtain our tree structures. In particular, five tree structures were developed: (a) four classification trees from which transition probabilities for nurse movement are determined based on the levels of X_S, X_T, X_{NT}, X_{DL1}, $\ldots$, X_{DLR}, X_A, X_{P1L}, and X_{P2L}; and (b) a regression tree to predict the amount of time a nurse will spend in a location based on the levels of X_S, X_T, X_{NT}, X_L, X_D, and X_A. A hypothetical regression tree is shown in Figure 3.1(a) to illustrate a prediction of the amount of time a nurse would spend in a location. At each node of the tree, a question is asked; a data point that satisfies the question will go left in the branching; and right if it fails to meet the criterion. Based on the levels of X_S, X_T, X_{NT}, X_L, X_D, and X_A, every data point ends up in one of the terminal nodes of the tree. Two hypothetical classification trees, one "location type tree" in Figure 3.1(b) and another "location tree" in Figure 3.1(c), are shown to illustrate the estimation of the probability that a location would be visited by a nurse. At each node of these trees, similar to the regression tree, a question is asked; data that satisfy the question will go left in the branching; and right if they fail to meet the criterion. The probability of going to a location type, i.e, unassigned patient room (0), assigned patient room (1), and non-patient room (2) is obtained from the location type classification tree based on the levels of X_S, X_T, and X_{NT}.

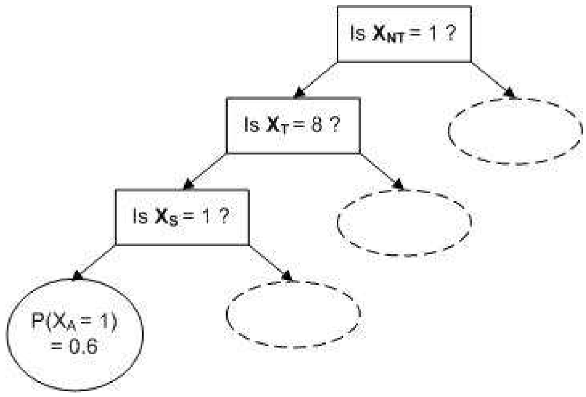
In the "location tree," built with a specific location type data, depending on the levels of X_S, X_T, X_{NT}, X_{DL1}, $\ldots$, X_{DLR}, X_A, X_{P1L}, and X_{P2L}, every data point ends up in one of the terminal nodes of the tree, where transition probabilities are estimated as follows:

$$\hat{p}(l/j) = \frac{1}{n(j)} \sum_{i=1}^{n(j)} I(i \in l), \tag{3.1}$$

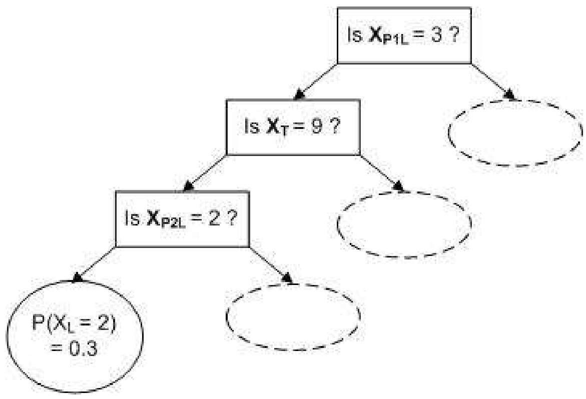
where, j = 1, $\ldots$, J are the terminal nodes of a "location tree"; $n(1), \ldots, n(J)$ are the numbers of observations in terminal nodes $1, \ldots, J$, respectively; l = 1, $\ldots$, N_L are the levels of X_L, i.e., the different locations in a given care unit, and I is an indicator function. The number of terminal nodes (J) differ for each tree. To be precise, J_0, J_1, and J_2 represent the number of



(a)



(b)



(c)

Figure 3.1. Tree structures: (a) A Hypothetical Regression Tree, (b) A Hypothetical "Location Type Tree", and (c) A Hypothetical "Location Tree".

terminal nodes of “location trees” for location types 0, 1, and 2, respectively. J_{LT} represent the number of terminal nodes of a “location type tree.” For a “location type tree”, $l = 0, \ldots, 2$ are the levels of X_A, i.e., unassigned patient room (0), assigned patient room (1), and non-patient room (2).

One useful outcome from using tree-based models is the variable importance scores that provide information on the influence of each variable to predict a response. Variable importance scores for all the trees are shown in Table 3.2. Variable importance scores for the regression trees estimating the amount of time a nurse will spend in a location are given in the first row. It can be seen that location is the most important variable. Primary diagnosis and assignment play a relatively more important role in medical/surgical II and high-risk Labor units than mom/baby and medical/surgical I units, and time (hour) of the day is more important than shift. Nurse type has about the same magnitude of importance across all the care units. Variable importance scores for the “location type trees” predicting a nurse′s next location type are shown in the second row of Table 3.2. It can be observed that nurse type for mom/baby and high-risk labor units, and time (hour) of the day for medical/surgical I & II units are the most important factors to predict the location type. Similar to the regression trees, time (hour) of the day is more important than shift. Variable importance scores of selected variables in the “location trees” predicting a nurse’s next location for different location types are shown in the last three rows of Table 3.2. It can be seen that the previous locations are the most important variables to predict the next location. Once again, time (hour) of the day is more important than shift. Variable importance scores of the variables $X_{AL1}, \ldots, X_{ALR}$ and $X_{DL1}, \ldots, X_{DLR}$ in the “location trees” are not presented here to make the table concise. As mentioned earlier, it is impossible even for a health care expert to observe all these intricate and subtle differences in the system without using a tool like CART.

While growing the trees, 10-fold cross validation was used for testing; class probability and least squares splitting rules were used for creating branching decisions of classification trees and regression trees, respectively. Prior probabilities of about 0.70 and 0.30 were used for assigned patient rooms (1) and non-patient rooms (2) as the classification system assumes 70% direct care and 30% indirect care for making nurse-patient assignments. Developing theories and models for justifying the choice of testing, splitting rules and prior probabilities for data-integrated simulations would be an interesting direction for future research.

3.3 Estimation of Time Spent Distribution

In classical regression tree predictions, the mean of each terminal node is used as the predicted value. In this research, to better reflect the actual distribution, for each terminal node of the regression trees, kernel density estimation (KDE) is used to estimate the probability density function for Time Spent (Y) by a nurse (under the conditions specified by that terminal node) in a particular location. Assume we have $n(j)$ independent observations $y_1, \ldots, y_{n(j)}$ for the random variable $Y(j)$ in the terminal node j. Let $K(\cdot)$ be a kernel function. Then the kernel density estimator $\hat{f}_{j,h}(y)$ at a point y is defined by equation (3.2) [72], as follows:

$$\hat{f}_{j,h}(y) = \frac{1}{h \times n(j)} \sum_{i=1}^{n(j)} K\left(\frac{y_i - y}{h}\right), \tag{3.2}$$

where, h is the bandwidth, which controls the “window” of neighboring observations that will highly influence the estimate at a given y. Sheather and Jones plug-in (SJPI) bandwidth estimates for h are used, as this method is one of the best for optimizing bandwidth ([45, 65, 64]); however, it should be noted that bandwidth selection is not precise and often an “art.” Tuning of the bandwidths based on our desired criteria is discussed in Section 3.3.2. Random variables $Y(1), \ldots, Y(J_R)$ denote the time spent (Y) in terminal nodes $1, \ldots, J_R$, respectively. Kernel density estimates with SJPI bandwidths were obtained for each terminal node of the regression trees. A typical plot with Gaussian and triangular kernels for each of the four care units is shown in Figure 3.2.

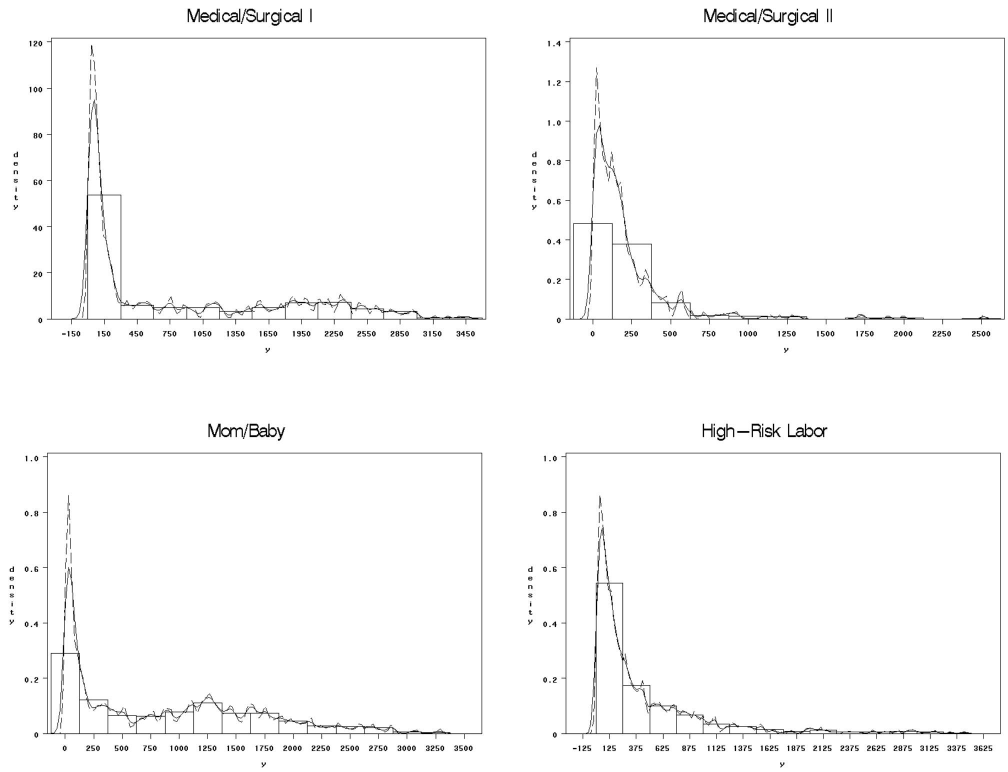


Figure 3.2. Kernel density estimates (Solid-Gaussian, and Broken-Triangular)..

3.3.1 Kernel choice

Kernel functions include uniform, Gaussian, triangular, Epanechnikov, quadratic, and cosinus. Gaussian and triangular kernels were chosen for this research as they are the most common kernels among modelers. Moreover, it is relatively easy to draw samples from Gaussian and triangular distributions, which is required for sampling the time spent random variable. SJPI bandwidth estimates [65] were calculated for each terminal node of the regression tree using SAS®. Figure 3.2 and the normal probability plots in Sundaramoorthi et al. [75] show that the time spent data have a long right tail, and a major portion of the data is concentrated near the left end of the distribution. Gamma distributions provided inadequate density estimates, motivating the use of KDE. To assess how well KDE represents the time spent distribution, 100,000 realizations of time spent data were generated from Gaussian and triangular kernel density estimates. The simulated data were compared with the actual data in four different ranges, i.e., (0, $M/2$], ($M/2$, M], (M, ($M + M/2$)], (($M + M/2$), ∞), where, M is the median of the actual data. Results from 100,000 simulated realizations of Gaussian and triangular kernels are shown in Table 3.3. There were 181, 109, 123 and 49 terminal nodes in the regression trees of medical/surgical I, medical/surgical II, mom/baby and high-risk labor units, respectively. The table shows that the triangular kernel wins more often than the Gaussian kernel irrespective of the care units and ranges. Among all the competitions i.e., $J_R \times 4$ competitions, the triangular won 75%, 80%, 82% and 78% of the competitions in medical/surgical I, medical/surgical II, mom/baby and high-risk labor units, respectively. A terminal node *win* was considered to be achieved if a kernel managed to win at least three ranges out of the four considered. Both the kernels were considered to be *tied* if they won two ranges each. The results on terminal node wins shown on the last two rows of Table 3.3 for each care unit further indicate that the triangular kernel is a better choice to model the Baylor data.

3.3.2 Bandwidth tuning

The accuracy of estimates depends more on choosing an appropriate bandwidth than on the choice of kernels [31, 71]. Bandwidth selection methods, including SJPI bandwidth estimates [65], try to find the optimal bandwidth that compromises a tradeoff between oversmoothness and undersmoothness of the estimated density. After obtaining bandwidths, we can decide to either decrease or increase the bandwidth size depending on the knowledge of the system. Data used in this project were collected over more than a six-month period and have about quarter to half a million observations for each care unit. With data collected over months, the different possible characteristics of the Baylor system will be well reflected in the simulation if the bandwidths are tuned to prefer a less smooth density estimate that reflects the data more accurately. In this research, if the fraction of simulated realizations in the ranges given in the previous section goes beyond $\pm$ 0.015 of the actual fraction of data, the bandwidth was iteratively decreased by one until this criterion was met. For example, the ninth terminal node of medical-surgical unit I shown in Table 3.4 has realizations that violated the $\pm$ 0.015 limit. After forty-four iterations of bandwidth tuning, all four ranges have fractions within the limit. This leads to a change of bandwidth at this particular terminal node to 8.46 from 52.46 and thus yields a less smooth kernel density estimate that is more representative of realizations of the time spent data.

3.4 Data-driven Simulation Model

To drive a nurse activity simulation, three essential questions are asked: (1) Which location type will a nurse go to next given her nurse type, shift, and time (hour) of the day? (2) Where will a nurse go next given her two past locations, next location type, shift, hour, nurse type, assignments, and diagnoses of all the patients? (3) How much time will she spend there? After an initial simulation run in which nurses visit their assigned patients for an initial assessment, transition probabilities obtained by equation (3.1) from the location type and location trees determine the next location a nurse will visit. Once a location type and in turn a location has been sampled for a given nurse, the amount of time she spends there is determined by a random sample of time spent y from the kernel density estimate at the appropriate terminal node in the regression tree. Clock time and the location variables are then updated. The level of X_T is changed if the updated time enters a new category. The levels of variables X_S and X_{NT} associated with a nurse remain unchanged throughout the shift. This process of sampling location type, location, and time spent is repeated until the shift ends.

Traditionally, in stochastic simulations, transition probabilities are obtained either subjectively or by looking at all the possible combinations of variable levels. In practice, simulation modelers combine states by making a variety of assumptions on their models. For instance, suppose a simulation expert were to model a system using a queuing network with one hundred servers. To model the system accurately, the modeler would need to determine whether the service times of each pair of servers were independent. This would require ten thousand tests of independence. If multiple servers were found to be dependent, then the modeler would have to group the servers into sets in which the servers are dependent. Then, the modeler would have to develop enormous multivariate distributions for each group that may consider tens of variables. In practice though, the modeler would likely make assumptions about the independence of these variables to limit the dimensionality of the multivariate distributions. If the system under consideration is complex, such as the care units in Baylor, then a subjective approach is unlikely to be accurate, and it will be impractical to implement an approach using all possible combinations of the levels of the simulation variables. In all possible combinations approach, the number of possible combinations (NPC) grows exponentially with the number of variables. In our problem, there are $N_S \times N_T \times N_{NT}$ combinations, denoted as NPC_{lt}, for sampling a location type and $N_S \times N_T \times N_{NT} \times N_A \times {N_L}^2 \times {N_D}^R \times 2^R$ combinations, denoted as NPC_l, for sampling a location. On the other hand, simulation models developed using trees, discussed in Section 3.2.1, require only J_{LT} terminal nodes for sampling a location type and J_0 + J_1 + J_2 terminal nodes for sampling a location based on the patterns extracted from the data. The more efficient the simulation, the more useful it will be for making real-time decisions. For example, prior to a shift, a charge nurse will determine whether the set of scheduled nurses is sufficient for the shift. If there is a shortage, a nurse supervisor will call a nurse agency to hire nurses for that shift. The simulation model can assist in this decision provided its run time is sufficiently fast. Differences between NPC_{lt} and J_{LT}, NPC_l and J_0 + J_1 + J_2 given in Table 3.5, demonstrate that our approach is significantly more efficient. All locations in the care units under consideration can be visited from any other location of that care unit. Even though some of these combinations of locations are unlikely to be visited in succession, without using a data mining tool like trees, it is not easy to justify ignoring or combining them.

Table 3.2. Variable importance scores for regression and classification trees

Tree Type	Med/Surg I	Med/Surg II	Mom/Baby	High-Risk Labor
Regression Tree				
X_L	100.00	100.00	100.00	100.00
X_D	11.20	60.02	7.54	70.42
X_{NT}	17.17	17.70	16.76	14.78
X_T	29.76	13.83	24.48	8.64
X_S	10.35	6.82	9.82	4.75
X_A	13.43	73.03	10.25	65.36
"Location Type" Tree				
X_{NT}	41.92	70.66	100.00	100.00
X_T	100.00	100.00	40.60	16.47
X_S	33.46	95.07	15.59	4.88
"Location" Tree (X_A = 1)				
X_{P1L}	100.00	68.36	100.00	100.00
X_{P2L}	67.21	100.00	72.95	76.26
X_{NT}	0.86	3.11	7.63	2.75
X_T	4.52	8.16	17.84	14.97
X_S	3.03	3.22	11.96	12.08
"Location" Tree (X_A = 2)				
X_{P1L}	100.00	100.00	100.00	100.00
X_{P2L}	52.56	48.53	66.37	82.15
X_{NT}	3.08	10.68	3.42	34.14
X_T	5.79	6.17	4.10	4.57
X_S	2.26	3.39	1.39	2.12
"Location" Tree (X_A = 0)				
X_{P1L}	100.00	96.47	100.00	100.00
X_{P2L}	65.35	100.00	68.35	94.09
X_{NT}	5.50	11.69	6.33	9.54
X_T	6.59	16.22	9.57	28.22
X_S	2.38	6.67	2.81	10.87

Table 3.3. Performance of Gaussian and triangular kernels

Care Unit	Gaussian	Triangular	Tie
MED/SURG I			
J_R=181			
Range I wins	26	155	
Range II wins	45	136	
Range III wins	77	105	
Range IV wins	36	145	
% wins	25%	75%	
Ter. node wins	13	135	33
% Ter. node wins	7%	75%	18%
MED/SURG II			
J_R=109			
Range I wins	15	94	
Range II wins	24	85	
Range III wins	31	78	
Range IV wins	18	91	
% wins	20%	80%	
Ter. node wins	7	92	10
% Ter. node wins	6%	85%	9%
MOM/BABY			
J_R=123			
Range I wins	13	110	
Range II wins	25	98	
Range III wins	31	92	
Range IV wins	18	105	
% wins	18%	82%	
Ter. node wins	9	104	10
% ter. node wins	7%	85%	8%
HIGH-RISK			
J_R=49			
Range I wins	9	40	
Range II wins	13	36	
Range III wins	19	30	
Range IV wins	3	46	
% wins	22%	78%	
Ter. node wins	3	38	8
% ter. node wins	6%	78%	16%

Table 3.4. Bandwidth tuning for terminal node 9 of medical/surgical unit I

Bandwidth Tuning	Sim. Fraction	Actual Fraction	Diff.
BEFORE			
h=52.46			
range I	0.070110	0.278986	0.208876
range II	0.083750	0.244842	0.161092
range III	0.075310	0.086039	0.010729
range IV	0.770830	0.390133	-0.380697
AFTER			
h=8.46			
range I	0.266580	0.278986	0.012406
range II	0.234510	0.244842	0.010332
range III	0.094890	0.086039	-0.008851
range IV	0.404020	0.390133	-0.013887

Table 3.5. Number of levels and combinations for different care units

Variable	Care Unit			
Level	Med/SurgI	Med/SurgII	Mom/Baby	High-Risk
N_S	5	5	5	5
N_T	24	24	24	24
N_{NT}	4	8	8	7
N_D	19	21	10	8
N_L	34	32	52	52
R	26	26	32	10
N_A	3	3	3	3
NPC_{lt}	480	960	960	840
J_{LT}	145	259	322	196
NPC_l	$> 10^{46}$	$> 10^{47}$	$> 10^{47}$	$> 10^{17}$
J_1	397	440	271	69
J_2	1816	1554	1194	96
J_0	262	268	118	38

CHAPTER 4

SIMNA EXPERIMENTS

4.1 Assignment Policies

A C++ program was written to build the tree structures given by CART and to run the simulation procedure explained in Section 3.2 for medical/surgical unit I with a thousand different random seeds. A test problem with four nurses and twenty one patients was considered. SIMNA tested four assignment policies, i.e., a clustered assignment and three assignments from Punnakitikashem et al. [62]–the random assignment, the heuristic assignment, and the optimal assignment using Benders' decomposition on a stochastic programming model. In the heuristic assignment, when the number of nurses divides into the number of patients evenly, all of the nurses get the same number of patients. The patient with the highest expected direct care time is arbitrarily assigned to a nurse. The patient with the second highest expected direct care time is then arbitrarily assigned to a second nurse, and so on. After assigning one patient for each nurse, in the second cycle of assignments, the patient with the lowest expected direct care time is assigned to the first nurse. The patient with the second lowest expected direct care time is assigned to the second nurse, and so on. This process of assignment is repeated until all the patients are assigned. In the test problem, each nurse was assigned to five patients by the heuristic method and the left over patient was arbitrarily assigned to the first nurse. In the clustered assignment, patients are assigned by location; that is, patients in consecutive rooms are assigned to the same nurse. In the test problem, the nurse assigned to the cluster closest to the nurses' station was assigned six patients, while the other nurses were assigned to five patients. Finally, the optimized assignment from Punnakitikashem et al. [62] seeks to balance the expected direct and indirect care provided by RNs. It should be noted that indirect care cannot be quantified from our data and is not represented in our simulation.

4.2 Test Results

The tested assignments and their results are shown in Tables 4.1 and 4.2. Total assigned direct care (TADC), total unassigned direct care (TUADC), total direct care (TDC), total time spent in non-patient locations (TNPL), and the walking time (Walk Time) are shown in the last five columns. TADC is the total duration of time a nurse spent with her assigned patients in the entire shift. TUADC is the total duration of time a nurse spent with unassigned patients. TDC is the sum of TADC and TUADC. TNPL is the the total time spent at locations other than patient rooms (e.g., the medical supply rooms, the charting rooms, the nurses' station, etc). In order to assess the balance of workload, we consider the ratios of maximum to minimum values for TADC, TDC, TDC for RNs, and walking time. Ratios closer to one indicate better balance. These ratios are given in Table 4.3. For balancing TADC, the heuristic assignment performs best and the random assignment performs worst. For balancing TDC, the heuristic assignment is worst, and the other three are similar to each other. For balancing TDC for RNs, the heuristic and optimal assignments perform best, and the random assignment performs worst. Finally, for balancing walking time, the clustered assignment performs better than the others. In particular for the optimal assignment, the sum of all nurses' TADC and TDC is higher than the other assignments, while the total walking time of the optimal assignment is less than that of the other assignments. Overall, the random assignment, not surprisingly, is the least desirable.

Prior to a shift, SIMNA results can aid the charge nurse in determining appropriate nurse-to-patient assignments. If the direct care time and balance in workload are not satisfactory, a nurse supervisor can call a nurse agency to hire nurses for that shift. Thus, SIMNA upon instal-

Table 4.1. SIMNA results for Med/Surg I from RANDOM and HEURISTIC initial assignments

Assignment Policy	Assigned Patient Locations	Assigned Patient Diagnoses	TADC (min)	TUADC (min)	TDC (min)	TNPL (min)	Walk Time (min)
RANDOM							
Nurse1 (LVN)	4, 6, 10, 17, and 18	1, 6, 16, 8 and 14	92	119	211	158	116
Nurse2 (RN)	3, 13, 15, 19, and 26	9, 16, 13, 12 and 15	152	127	279	118	87
Nurse3 (RN)	1, 7, 14, 16, and 20	14, 10, 3, 4 and 8	220	84	304	94	87
Nurse4 (RN)	2, 5, 8, 9, 23, and 24	13, 8, 3, 6, 8, and 15	185	127	312	83	88
Total			651	459	1107	455	379
HEURISTIC							
Nurse1 (LVN)	9, 10, 13, 14, 23, and 26	6, 16, 16, 3, 8, and 15	122	74	196	173	115
Nurse2 (RN)	5, 7, 15, 16, and 20	8, 10, 13, 4 and 8	209	95	304	93	87
Nurse3 (RN)	2, 4, 6, 8, and 19	13, 1, 6, 3 and 12	163	149	312	83	89
Nurse4 (RN)	1, 3, 17, 18, and 24	14, 9, 8, 14 and 15	192	126	318	83	84
Total			688	446	1132	434	376

lation in hospitals will aid charge nurses and management to make decisions about assignments and the nurse work force based on the dynamics learned from the system itself.

Table 4.2. SIMNA results for Med/Surg I from CLUSTER and STOCHASTIC PROGRAMMING initial assignments

Assignment Policy	Assigned Patient Locations	Assigned Patient Diagnoses	TADC (min)	TUADC (min)	TDC (min)	TNPL (min)	Walk Time (min)
CLUSTER							
Nurse1 (LVN)	1, 4, 14, 17, 20, and 24	14, 1, 3, 8, 8, and 15	194	16	210	171	102
Nurse2 (RN)	3, 6, 8, 10, and 13	9, 6, 3, 16 and 16	172	139	311	83	90
Nurse3 (RN)	2, 16, 19, 23, and 26	13, 4, 12, 8 and 15	125	158	283	106	94
Nurse4 (RN)	5, 7, 9, 15 and 18	8, 10, 6, 13 and 14	107	195	302	89	94
Total			600	520	1107	451	381
STOCHASTIC PROGRAMMING							
Nurse1 (LVN)	10, 13, 14, 16 and 17	16, 16, 3, 4 and 8	164	45	209	172	104
Nurse2 (RN)	3, 7, 20, 24 and 26	9, 10, 8, 15 and 15	222	85	307	101	75
Nurse3 (RN)	1, 2, 4, 6, 8, and 23	14, 13, 1, 6, 3, and 8	193	120	313	82	89
Nurse4 (RN)	5, 9, 15, 18 and 19	8, 6, 13, 14 and 12	115	187	302	89	94
Total			696	441	1132	446	363

Table 4.3. Maximum-to-minimum ratios for TADC, TDC, and Walk time

Assignment Policy	TADC	TDC	TDC (RNs)	Walk Time
Random	2.39	1.48	1.12	1.33
Heuristic	1.71	1.62	1.05	1.37
Cluster	1.81	1.48	1.10	1.13
Stochastic Prog.	1.93	1.50	1.04	1.39

CHAPTER 5

SIMULATION VALIDATION AND SIMULATION-BASED OPTIMIZATION

5.1 Simulation Validation

Interestingly, it was observed that the "40-20-40" rule [57, 68] still holds well in our data-integrated simulation modeling. According to this rule, 40% of the effort in a simulation project is devoted to understanding, conceptualizing the system, and formulating the model; 20% of the effort is devoted to make the actual simulation model, and the last 40% of the effort includes analysis, calibration and validation of the simulation model. Most of the first and last 40% of the project, i.e., understanding, formulation, conceptualization, calibration and validation, are conducted through data mining. In this chapter, simulation results are compared with the actual data to illustrate the validity of the simulation model.

Among different steps in the traditional simulation modeling, validation is an important step in which accuracy of the model is verified by comparing it to the actual system. Depending on the magnitude of the discrepancy, if needed, the simulation model would be calibrated based on the insights gained by the modeler from the simulation output analysis. The following were among several common validation steps performed as part of the validation process in this data-integrated simulation modeling approach.

1. Tree Structure: The tree structures were printed before the first scenario of simulation run to ensure accurate building of trees for simulation runs.
2. Shift Duration: TDC, TNPL, and WALK TIME were added for each nurse to check with the entire shift duration.
3. Kernel Density: The kernel and bandwidth validations, presented in section 3.3, ensured a reliable approximation of data in regression trees.

4. Cumulative Density: The cumulative densities of kernel distributions in each terminal node were printed to check if they were close to one.

The primary objective of this research is to provide a tool to aid charge nurses in making balanced nurse-patient assignments. In this research, the balance of workload and performance of nurses were judged based on performance measures TADC, TDC, TNPL, and WALK TIME that were introduced in chapter 4 and shown in tables 4.3, 4.1, and 4.2. As part of the main validation, actual TADC, TDC, TNPL, and WALK TIME of fifteen arbitrarily chosen nurses were compared with that of simulated data. The fifteen arbitrarily chosen nurses with their assigned patients' and shift information were simulated over one thousand different scenarios. The comparison between mean values of performance measures from a thousand scenarios and the actual data are plotted in figure 5.1.

Figure 5.1(a) specifically shows the comparison of actual and simulated TADC. In the TADC comparisons, as well as TDC, TNPL, and WALK TIME comparisons shown in figures 5.1(b), 5.1(c), and 5.1(d) , purple curves represent the mean from the one thousand simulation scenarios while dark blue curves represent actual data. The yellow and light blue curves represent the first and ninty ninth percentiles of the simulation scenarios. Ideally, it is desirable to have the dark blue curve in between the yellow and light blue curves overlapping with the pink curve. In TADC comparisons, the mean of the simulation scenarios approximates the actual data closely by picking up the pattern as well as the magnitude. Among the different performance measures used in this research, TADC is the most important as it measures the amount of assigned direct care provided by nurses and directly impacts patient care and continuity of care.

Simulated and actual TDCs, shown in figure 5.1(b), compare another important performance measure in terms of nurse work load as well as patient care. It can be seen that, the mean TDC from simulation approximates the pattern of actual data closely. However, the plots show that TDC from simulation over-estimates the TDC of actual data. If the objective were to predict the TDC of nurses in isolation without any comparison, it would be desired to calibrate the simulation to reduce the magnitude of TDC. However, this research seeks only the balance, as shown in table 4.3, by comparing the maximum of a performance to the corresponding minimum. The resultant max-min ratio will not be altered by the discrepancy in the magnitude, neither by over-estimation or under-estimation, as long as the pattern of the performance measure in simulation matches with the actual data as shown for TDC in figure 5.1(b).

Figure 5.1(c) shows the comparison of actual and simulated TNPL. It can be seen from the figure that the simulation model provides TNPL that matches the pattern of actual data and hence provides reliable max-min ratio for TNPL. However, the plots show that TNPL from simulation under-estimates the TNPL of actual data and should not be used to interpret the magnitude of TNPL of individual nurses in isolation. Simulated and actual WALK TIME, shown in figure 5.1(d), compare the performance measure that accounts for the amount of time a nurse walks during the entire shift. In this research, a deterministic time is added depending on the distance between two locations a nurse walks in the simulation. In reality, these walk-times are stochastic as different nurses at different times would spend different amounts of time walking between the same locations. Figure 5.1(d) shows the comparison of actual and simulated WALK TIME. It can be observed that simulated WALK TIMEs have less variability across the nurses. It also shows that the simulation approximates the magnitude of real walking time closely.

The above discussion shows that performance measures of the simulation model approximate the pattern of real data, and to a certain extent the magnitude. Hence, it represents the actual system well enough to arrive at conclusions about the nurse work load balance in terms of the ratios introduced in table 4.3 without further calibration of the simulation.

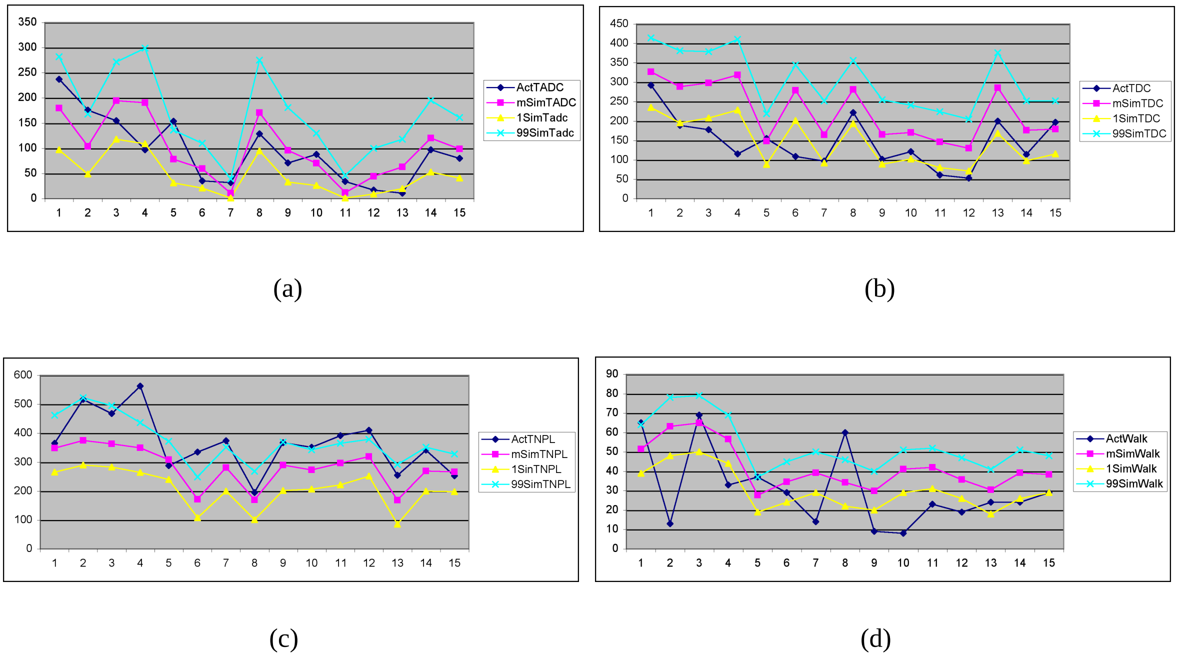


Figure 5.1. Comparison of Actual data with Simulated data: (a) Actual Vs. Simulated TADC, (b) Actual Vs. Simulated TDC, (c) Actual Vs. Simulated TNPL, and (d) Actual Vs. Simulated WALK TIME.

5.2 Simulation-based Optimization

In addition to evaluating initial assignments at the beginning of a shift, optimizing the assignment of new patient-admits during the shift is another interesting topic that was researched in this dissertation. Recently, formulating and solving Markov decision problems using a simulator have become common and successful [37, 15]. A typical Markov decision problem (MDP) would have the following components:

1. State: The "state" describes the status of a system under consideration. For example, specific values of the shift, the time of day, the nurse type, the current and previous locations of nurse, the nurse-patient assignments, the patient diagnosis, the patient acuity, and the patient location variables can be considered as the state that describes the system.
2. Action: Assignment of a newly admitted patient to a nurse is defined to be the "action" in this research.

3. Transition Probability: Transition Probabilities determine transitions of the system from one state to another. Assume an action *a* selected in state *i* transfers the system to state *j* with probability *p(i,a,j)*. This quantity is an example of a transition probability. Collection of all such transition probabilities for all possible state transitions is required to capture the dynamics of the system modeled.
4. Policy: A policy helps to take an action based on the state of the system. For example, when a new patient is admitted during a shift, there could be different policies used to make the assignment based on the state. A policy that maximizes the sum of TADCs of nurses, shown in equation (5.4), would increase patient care. Two policies that balance nurse workload are presented in section 5.2.1 of this chapter.
5. Performance Measure: A performance measure quantifies the performance of a policy. For a patient care improvement problem, the sum of TADCs of all nurses could be used to judge the performance of the policy.

In the late 1950's, a mathematical technique called Dynamic Programming (DP) was formulated by Bellman that could solve MDPs [12]. Since then, DP has evolved and found several aplications that it could solve [15, 14, 69, 86, 25, 79, 80, 22, 21, 23]. The theory and solution technique of DP also evolved all these years. Most of the solution techniques boil down to either approximating or reducing the Bellman optimality equation (5.1) for a computationally possible solution.

$$J^*(i) = \min_{a\in A(i)} \left[\bar{c}\,(i,a) + \sum\nolimits_{j=1}^{\|S\|} p(i,a,j) J^*(j)\right] \forall i \in S. \tag{5.1}$$

where:

1. *S* is the set of all possible states.
2. *A(i)* is the set of actions available for state *i*.
3. J^*s are the unknown optimal values associated with each element in *S*.

4. $\bar{c}(i,a)$ is the immediate expected cost in state *i* when action *a* is selected.
5. *p(i,a,j)* is the transition probability for the state transition from *i* to *j* when the action a is selected in state *i*.

Applying a classical method of solving equation (5.1), for optimizing the assignment of a newly-admitted patient, is impossible due to the high dimensional state space and unavailability of transition probabilities. In such situations, when transition probabilities are not available, a valid simulation model can be utilized to solve equation (5.2) - an equivalent of equation (5.1)- by the Q-factors method. Refer [37, 14] for a comprehensive review on Q-Factors methods.

$$J^*(i) = \min_{a \in A(i)} \left[E\left(c\left(i,a\right)\right) + E\left(J^*(j)\right)\right] \forall i \in S. \tag{5.2}$$

Equation 5.2 can be further simplified to equation (5.3).

$$J^*(i) = \min_{a \in A(i)} E\left(c\left(i,a\right) + J^*(j)\right) \forall i \in S. \tag{5.3}$$

In the new-admit patient-nurse assignment optimization problem, if the objective were to maximize the sum of TADCs of the nurses for the entire shift, the new-admit patient-nurse assignment optimization can be expressed as,

$$J^*(i) = \max_{a \in A(i)} \left[\sum\nolimits_{n=1}^{N} TADC_n\left(i,a,i+1\right)\right] + E\left(J^*(i+1)\right) \forall i \in S. \tag{5.4}$$

In equation (5.4), N is the total number of nurses working in that shift, and $TADC_n(i,a,i+1)$ denotes $TADC$ of nurse n from i to the state $i+1$ when the next arrival takes place, given optimal assignment a for the newly-admitted patient at i. It has to be noted that in equation (5.4), simplified notations *i* and *i+1* represent high dimensional states determined by specific values of shift, time of day, nurse type, current and previous locations of nurse, existing nurse-patient assignments, patient diagnosis, patient acuity, and patient location variables. The action of assigning a newly admitted patient to a specific nurse is represented by *a*. It should be also noted that an action is necessary only when a new patient is admitted and not necessarily in all possible states. Therefore, $i = 1, \ldots, l$ are the states when an action is required. In this notation, there are l remaining new admits, while solving for the current new-patient admit in i.

As mentioned earlier, with a simulation model available, a computational optimization technique called Q-Factors is an attractive approach to solve equation (5.4). The fundamental idea of this approach is to store quantities *Q(i,a)s* called Q-Factors for each state-action combination and update them based on the progress of the simulation. In the beginning, these Q-Factors are usually initialized to zero. Then for each action selected, the simulation is allowed to transition to the next state, and based on the performance measure, the Q-Factors are updated. For the patient care improvement problem, a state-action pair yielding a larger sum of TADCs of all nurses would be rewarded by increasing the corresponding Q-Factor. State-action pairs yielding smaller sum of TADCs would be punished by reducing the corresponding Q-Factors. The same policy of rewarding and punishing has to be repeated for sufficiently large number of state-action visits. At the end, action that provided the highest Q-Factor would be declared as optimum.

The key for achieving the true or near optimum in the Q-Factors method depends on the choice of the so-called "sufficiently large number" for state-action pair visits. In the problem of optimizing assignment of newly-admitted patient, the number of state-action pairs grow exponentially due to stochastic arrival of patients (admit time) with unknown probability distribution for diagnosis and acuity. Such a huge number of state-action pairs makes it computationally impossible to have enough simulation scenarios to obtain reliable Q-Factors.

5.2.1 Assignment Policies

Even though increasing patient care is an important objective, in this research it is implicitly assumed that balancing nurse workload will help improve patient care, and hence the max-min TADC ratio was chosen to be the performance measure. In addition to the computational issues raised in the previous section, the max-min TADC ratio is not additive and consequently, the nurse workload balancing problem cannot be formulated like equation (5.4). For these reasons, methods like simple enumeration, classical DP, and Q-Factors are ruled out for this research.

Among the two expected values in equation (5.2), the first one incorporates the immediate cost (reward) i.e., in a sense, it accounts for the past and immediate present. The second expected value, which approximates the future, for a current decision is impossible to approximate from simulation due to a huge number of state-action pairs. In the nurse-patient assignment problem, the difficulty boils down to the estimation of $TADC(i, a, i+1)$. While solving for optimal assignments in i, it will require huge number of simulation runs to optimize assignments $a(i+1)\ldots a(l)$. For this reason, an alternate policy that groups both the expected values of equation (5.2) together, represented by equation (5.5), is developed in this research. It is called OPT referring to its root in Bellman optimality equation.

$$J^{\wedge}(i) = \min_{a \in A(i)} E\left(\frac{(TADC\,(0, a(0), i) + TADC\,(i, a, T))_{max}}{(TADC\,(0, a(0), i) + TADC\,(i, a, T))_{min}}\right) \forall i \in S. \tag{5.5}$$

In equation (5.5),$TADC_n(0, a(0), i)$ denotes the $TADC$ of nurse n from beginning of the shift until i, given assignment $a(0)$ made at the beginning of the shift. $TADC(i, a, T)$ can be expanded as $TADC(i, a(i), i+1) + TADC(i+1, a(i+1), i+2) + \ldots + TADC(l, a(l), T)$. Where, T is the state of the system at the very end of the shift. It has to be noted that while solving for the assignment at state *i*, the future assignments required to obtain $TADC(i+1, a(i+1), i+2) + \ldots + TADC(l, a(l), T)$ were determined by a heuristic policy referred as HEU. The HEU policy simply assigns a newly-admitted patient to the nurse who had the least TADC among all the nurses fifteen minutes prior to a new patient admission. It is assumed in this research, and also common in reality, that the time of admit, patient diagnosis, and patient acuity are known to the decision maker -in this case a charge nurse- at least fifteen minutes before the actual admission. Therefore, the decision maker can use either HEU by itself or OPT to decide which nurse would get the new patient.

To analyze the performance of OPT and HEU, fifty problems with different initial states were considered. Admissions of two, three, four, five, and six patients were considered. The fifty problems were designed in such a way, shown in table 5.1, to have ten problems for each shift and ten problems for each number of admits. The number of problems for each combination of shift and number of new admits were arbitrarily chosen with admit rates, shown in table 5.2, in consideration. It is determined from patient data that on average there are nine patient-admits for a given day. While solving an assignment, the future admits were simulated using a poisson process with the arrival rates, for different time periods in simulation, determined by the average number of patient admits per day and admit rates for specific time period shown in table 5.2.

Table 5.1. Fifty Problem Instances

	# of New Admits				
Shift	2	3	4	5	6
WEEK					
Day	2	5	3	0	0
Evening	0	0	2	4	4
Night	7	2	1	0	0
WEEK END					
Day	0	0	0	5	5
Night	1	3	4	1	1

For all the fifty problems considered, the empty patient rooms available for new admits were selected randomly. The number of empty rooms, in a given problem, was chosen to

Table 5.2. Patient Admit Rate

6am to 2pm	2pm to 6pm	6pm to Midnight	Midnight to 6am
12%	70%	16%	2%

be the same as the number of new admits. The diagnosis and acuity of patients present at the beginning of the shift as well as newly-admitted patients were chosen randomly. While obtaining assignments for these fifty problems, admission times of the patients - for whom an assignment has to be determined - were chosen arbitrarily and remained unknown until fifteen minutes prior to the actual admit. Then the fifty assignments obtained from OPT and HEU were simulated without other admits to obtain average max-min TADCs for the entire shift. Assignments from a third random policy, refered as RAND, were also simulated to judge the degree of improvement that can be achieved using “smarter” policies like HEU and OPT. Average max-min TADCs from one thousand simulation scenarios, for each of the fifty assignments, are presented in tables 5.3 and 5.4.

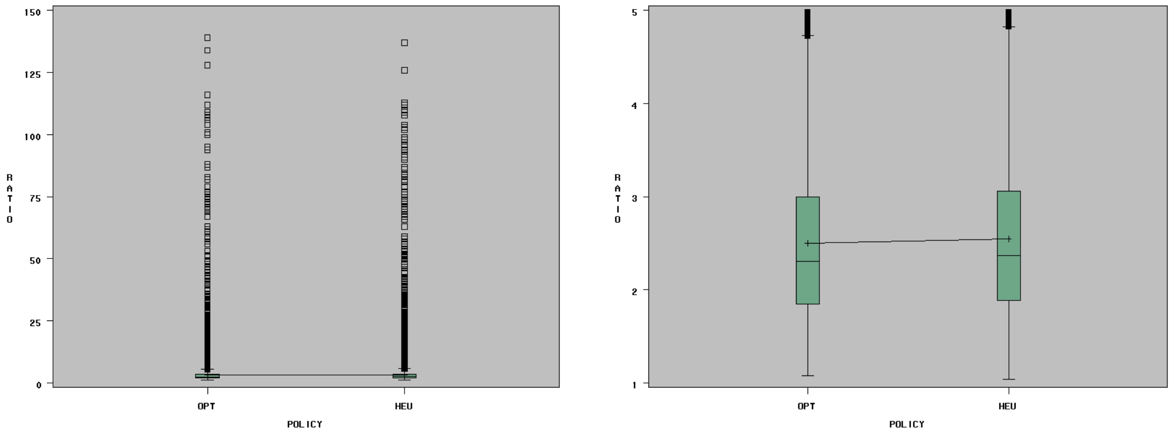
In tables 5.3 and 5.4, the first column represents the problem instances presented in table 5.1. The second column presents the average max-min TADCs from the three policies evaluated. In the third column, the policy yielding the smallest average max-min TADC is declared as the winner. It can be observed from the third column that OPT won thirty of the fifty problems while HEU won seventeen of them. Not surprisingly, RAND managed to win just three of the fifty problems. In the last column, wins are determined by a stricter criterion. According to that criterion, a win is considered to be achieved only if a policy yielded an average max-min TADC ratio smaller than the other two policies by at least one tenth - meaning there was roughly ten percent or greater reduction of workload imbalance compared to the other two policies. The instances, when OPT, HEU, and RAND yielded ratios that were within one tenth of each other, were declared as tie. It can be observed from the fourth column that with the modified criterion, OPT won seventeen times while HEU won five times. RAND policy won two of the fifty problems. It is clear from these results that HEU and OPT consistently perform better than RAND.

While considering averages to determine the performance of policies, it is important to account for the variability associated with each policy. Boxplots are provided in figure 5.2 to illustrate the spread of data from OPT and HEU policies. Because of outlier scenarios, the scale of boxplots in figure 5.2(a) is extended leaving it hard for a reader to observe the differences in the plots from OPT and HEU. In figure 5.2(b), the max-min TADC values above five were removed to get plots that are comparable. After this removal, OPT and HEU policy had 45,429 and 45,089 max-min TADCs, sufficiently large number of data points to make a comparison of spread, respectively. One could well argue that, in reality, it is unlikely to have an imbalance of a magnitude that would result in a value of five or more for max-min TADCs. It has to be noted that all the fifty problems did not consider balancing nurse-patient assignment at the beginning of the shift and hence high values for max-min TADCs cannot be ruled out. A high value for max-min TADCs is further justified by the value obtained for TADC under RANDOM initial assignments shown in table 4.3. However, individual boxplots from each of the fifty instances, shown in figures 5.3 to 5.17, are ploted after removal of five or higher max-min TADCs for comparability of spread in OPT and HEU data. Specifically, plots in figure 5.3to 5.17, ignoring RAND policy, show the boxlots of eighteen wins of OPT, five wins of HEU, and twenty seven ties between OPT and HEU, respectively. Even though these plots are provided just to illustrate the spread of max-min TADCs, it can be observed that the performance of policies remain the same with a lesser magnitude for differences between OPT and HEU.

5.2.2 Statistical Significance

In section 5.2.1, performances of OPT, HEU and RAND were analyzed from a practical stand point of view by comparing the average and spread of max-min TADCs. In that analysis, it was found that the OPT policy is the most successful while the RAND policy is the least successful among the fifty problem instances considered. However, it is necessary to perform statistical analysis to determine conclusive evidence regarding the difference in performances among the policies. In order to understand the statistical difference among the policies, 95% and 99% confidence intervals (CI) were constructed in tables 5.5, 5.6, 5.7, and 5.8. In particular, tables 5.5 and 5.6 show the confidence intervals for the mean of RAND - HEU. In these tables, RAND is declared as the winner if both the upper and lower limits are negative. The negative limits indicate a higher max-min TADC from the HEU policy compared to the RAND policy. Similarly, HEU is declared as the winner if both the upper and lower limits are positive. The instances with zero included in the confidence intervals are declared as ties. It can be observed from these tables that HEU won thirty-eight of the fifty problem instances while RAND won just once in 95% confidence intervals. In eleven instances, the confidence intervals included zero and hence were declared as Ties. With 99% confidence intervals, HEU won thirty-four times while RAND winning again just once. The rest of the fifteen instance ended as Tie between HEU and RAND. From these analysis, as expected, RAND can be safely concluded as the least desired policy.

In tables 5.7 and 5.8, confidence intervals for the mean of HEU - OPT are shown. In these tables, the HEU policy is declared as the winner if both the upper and lower limits are negative. The OPT policy is declared as the winner if both the upper and lower limits are positive. With 95% confidence intervals, OPT won fifteen times while HEU won four times of all the test problem instances. The rest of the thirty-one instances ended as Tie between OPT and HEU. With 99% confidence intervals, OPT won ten times while HEU won two times. The remaining thirty-eight problem instances were declared as tied as zero was included in the confidence intervals. It can be viewed that OPT performed at least as good as HEU in forty-six and forty-eight instances with 95% and 99% confidence intervals, respectively.



(a) (b)

Figure 5.2. Boxplots of max-min TADCs from OPT and HEU: (a) All 50,000 max-min TADCs and (b) Max-min TADCs that are less than 5.

The OPT policy considers both the past and the future workload of nurses for a nurse-patient assignment decision while HEU considers only the past workload. Intutively, assignments obtained from OPT would perform better than HEU if a reliable estimation of future was used while solving for the assignments with the OPT policy. From our above analyses, not surprisingly, the OPT policy was found to work better than HEU and RAND policies.

Table 5.3. Outcome of policy evaluations with two, three, and four patients

# Patients, Shift, Instance	Av. Ratio			Winning Policy	$\geq 10\%$ Win
2, 1, 1	3.206	3.146	3.149	HEU	Tie
2, 1, 2	2.690	2.945	3.295	OPT	OPT
2, 3, 1	3.034	3.267	3.183	OPT	OPT
2, 3, 2	4.292	4.362	4.361	OPT	Tie
2, 3, 3	3.836	4.141	5.310	OPT	OPT
2, 3, 4	4.478	5.730	4.469	RAND	Tie
2, 3, 5	4.208	4.496	4.290	OPT	Tie
2, 3, 6	3.692	3.907	3.949	OPT	OPT
2, 3, 7	5.871	5.172	6.586	HEU	HEU
2, 5, 1	2.102	2.229	5.511	OPT	OPT
3, 1, 1	3.069	3.020	3.709	HEU	Tie
3, 1, 2	3.562	3.564	3.863	OPT	Tie
3, 1, 3	3.521	3.450	5.412	HEU	Tie
3, 1, 4	2.712	2.678	2.988	HEU	Tie
3, 1, 5	4.162	3.770	4.706	HEU	HEU
3, 3, 1	4.007	4.101	4.432	OPT	Tie
3, 3, 2	6.792	5.584	6.660	HEU	HEU
3, 5, 1	3.201	3.561	3.318	OPT	OPT
3, 5, 2	2.439	2.250	5.050	HEU	HEU
3, 5, 3	2.238	2.225	3.188	HEU	Tie
4, 1, 1	3.935	4.250	4.790	OPT	OPT
4, 1, 2	2.742	3.131	3.867	OPT	OPT
4, 1, 3	4.213	4.057	7.123	HEU	HEU
4, 2, 1	2.568	3.758	4.186	OPT	OPT
4, 2, 2	3.499	3.422	3.320	RAND	RAND
4, 3, 1	2.702	3.043	3.411	OPT	OPT
4, 5, 1	2.657	2.612	4.391	HEU	Tie
4, 5, 2	2.154	2.165	3.474	OPT	Tie
4, 5, 3	2.574	2.567	4.402	HEU	Tie
4, 5, 4	2.341	2.326	4.382	HEU	Tie

Table 5.4. Outcome of policy evaluations with five and six patients

# Patients, Shift, Instance	Av. Ratio			Winning Policy	$\geq 10\%$ Win
5, 2, 1	4.093	4.080	3.936	RAND	RAND
5, 2, 2	2.881	2.900	8.267	OPT	Tie
5, 2, 3	2.946	3.139	3.216	OPT	OPT
5, 2, 4	4.000	4.413	6.720	OPT	OPT
5, 4, 1	1.972	1.932	4.769	HEU	Tie
5, 4, 2	1.844	1.888	3.936	OPT	Tie
5, 4, 3	1.924	1.977	3.650	OPT	Tie
5, 4, 4	2.084	2.183	5.443	OPT	Tie
5, 4, 5	2.034	2.041	5.417	OPT	Tie
5, 5, 1	2.601	2.522	5.110	HEU	Tie
6, 2, 1	2.635	2.653	3.150	OPT	Tie
6, 2, 2	3.183	3.749	4.838	OPT	OPT
6, 2, 3	3.864	3.928	5.059	OPT	Tie
6, 2, 4	3.309	3.237	3.571	HEU	Tie
6, 4, 1	1.872	1.929	6.645	OPT	Tie
6, 4, 2	3.017	3.159	10.030	OPT	OPT
6, 4, 3	1.846	2.388	4.879	OPT	OPT
6, 4, 4	2.468	2.381	8.326	HEU	Tie
6, 4, 5	2.409	2.743	16.223	OPT	OPT
6, 5, 1	2.505	2.523	5.762	OPT	Tie

Table 5.5. Confidence Intervals for means of RAND-HEU with two, three, and four new incoming patients

# Patients, Shift, Instance	RAND-HEU 95% CI		RAND-HEU 99% CI		Winning Policy 95% CI	Winning Policy 99% CI
2, 1, 1	-0.241	0.247	-0.317	0.324	Tie	Tie
2, 1, 2	0.049	0.651	-0.046	0.745	HEU	Tie
2, 3, 1	-0.448	0.280	-0.562	0.394	Tie	Tie
2, 3, 2	-0.534	0.532	-0.701	0.698	Tie	Tie
2, 3, 3	0.524	1.813	0.322	2.015	HEU	HEU
2, 3, 4	-1.938	-0.585	-2.150	-0.373	RAND	RAND
2, 3, 5	-0.667	0.254	-0.811	0.399	Tie	Tie
2, 3, 6	-0.324	0.408	-0.439	0.523	Tie	Tie
2, 3, 7	0.745	2.082	0.535	2.292	HEU	HEU
2, 5, 1	2.789	3.775	2.634	3.930	HEU	HEU
3, 1, 1	0.418	0.961	0.333	1.046	HEU	HEU
3, 1, 2	-0.148	0.746	-0.288	0.886	Tie	Tie
3, 1, 3	1.355	2.569	1.165	2.759	HEU	HEU
3, 1, 4	0.159	0.462	0.111	0.510	HEU	HEU
3, 1, 5	0.417	1.456	0.254	1.618	HEU	HEU
3, 3, 1	-0.193	0.855	-0.357	1.019	Tie	Tie
3, 3, 2	0.282	1.870	0.033	2.119	HEU	HEU
3, 5, 1	-0.548	0.064	-0.644	0.160	Tie	Tie
3, 5, 2	2.413	3.186	2.292	3.307	HEU	HEU
3, 5, 3	0.691	1.236	0.606	1.321	HEU	HEU
4, 1, 1	0.009	1.070	-0.157	1.237	HEU	Tie
4, 1, 2	0.537	0.935	0.475	0.997	HEU	HEU
4, 1, 3	2.315	3.817	2.080	4.052	HEU	HEU
4, 2, 1	0.100	0.757	-0.004	0.860	HEU	Tie
4, 2, 2	-0.325	0.121	-0.395	0.191	Tie	Tie
4, 3, 1	0.118	0.617	0.039	0.696	HEU	HEU
4, 5, 1	1.510	2.048	1.426	2.132	HEU	HEU
4, 5, 2	1.163	1.454	1.117	1.500	HEU	HEU
4, 5, 3	1.474	2.196	1.361	2.309	HEU	HEU
4, 5, 4	1.776	2.336	1.689	2.423	HEU	HEU

Table 5.6. Confidence Intervals for means of RAND-HEU with five and six new in-coming patients

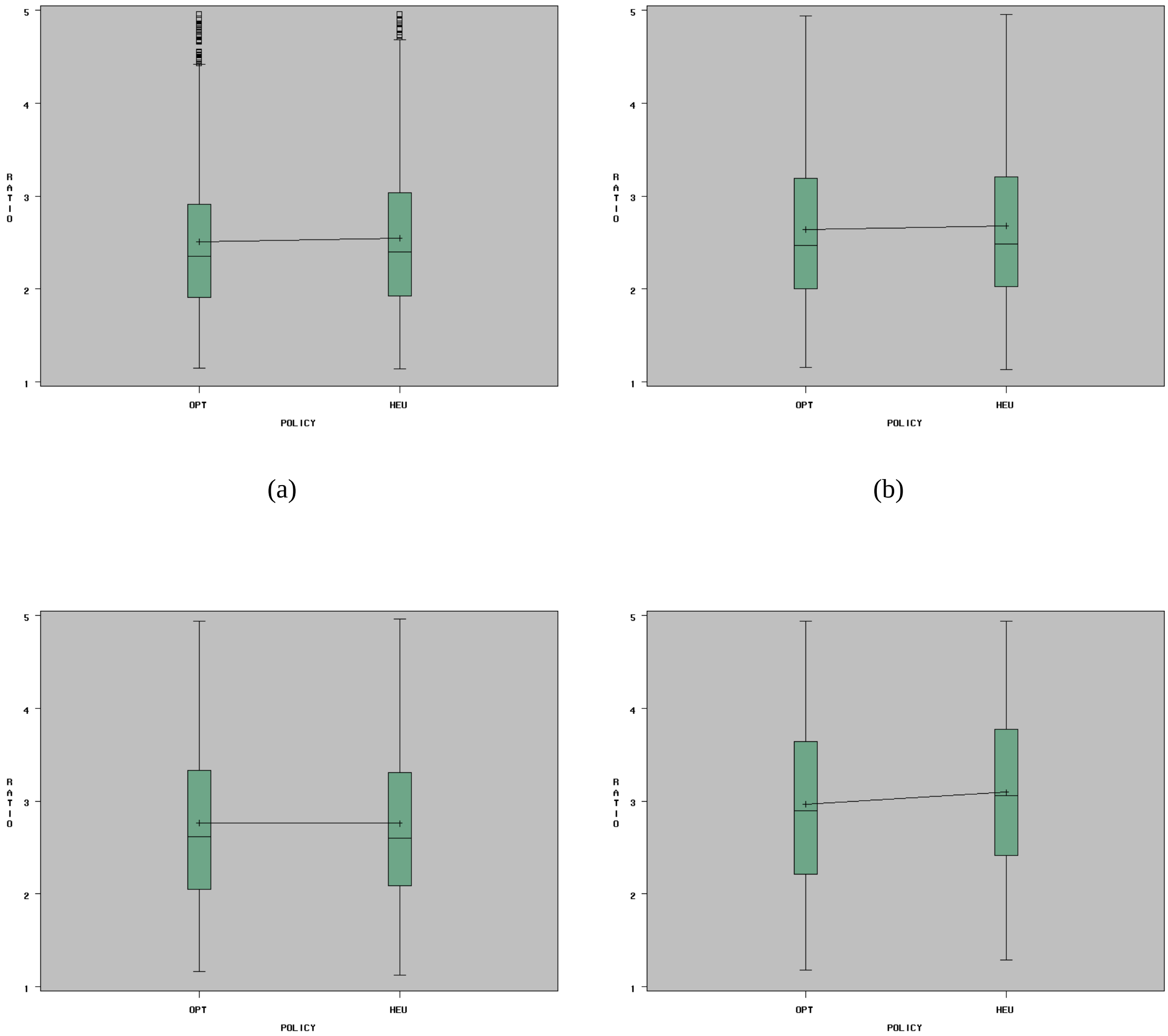
# Patients, Shift, Instance	RAND-HEU 95% CI		RAND-HEU 99% CI		Winning Policy 95% CI	Winning Policy 99% CI
5, 2, 1	-0.583	0.295	-0.720	0.432	Tie	Tie
5, 2, 2	4.489	6.244	4.214	6.519	HEU	HEU
5, 2, 3	-0.128	0.282	-0.192	0.347	Tie	Tie
5, 2, 4	1.551	3.062	1.314	3.299	HEU	HEU
5, 4, 1	2.424	3.250	2.294	3.380	HEU	HEU
5, 4, 2	1.883	2.214	1.831	2.265	HEU	HEU
5, 4, 3	1.452	1.893	1.383	1.963	HEU	HEU
5, 4, 4	2.711	3.810	2.539	3.982	HEU	HEU
5, 4, 5	2.921	3.831	2.779	3.974	HEU	HEU
5, 5, 1	2.149	3.028	2.011	3.166	HEU	HEU
6, 2, 1	0.205	0.790	0.113	0.882	HEU	HEU
6, 2, 2	0.496	1.683	0.310	1.869	HEU	HEU
6, 2, 3	0.450	1.812	0.236	2.026	HEU	HEU
6, 2, 4	0.053	0.614	-0.035	0.701	HEU	Tie
6, 4, 1	4.184	5.249	4.017	5.416	HEU	HEU
6, 4, 2	6.076	7.666	5.827	7.915	HEU	HEU
6, 4, 3	2.115	2.866	1.997	2.984	HEU	HEU
6, 4, 4	5.281	6.608	5.073	6.816	HEU	HEU
6, 4, 5	11.968	14.990	11.494	15.464	HEU	HEU
6, 5, 1	2.861	3.617	2.743	3.735	HEU	HEU

Table 5.7. Confidence Intervals for means of HEU-OPT with two, three, and four new incoming patients

# Patients, Shift, Instance	HEU-OPT 95% CI		HEU-OPT 99% CI		Winning Policy 95% CI	Winning Policy 99% CI
2, 1, 1	-0.305	0.184	-0.382	0.261	Tie	Tie
2, 1, 2	0.039	0.470	-0.029	0.538	OPT	Tie
2, 3, 1	-0.069	0.536	-0.164	0.631	Tie	Tie
2, 3, 2	-0.485	0.625	-0.660	0.799	Tie	Tie
2, 3, 3	-0.220	0.830	-0.385	0.995	Tie	Tie
2, 3, 4	0.521	1.985	0.291	2.214	OPT	OPT
2, 3, 5	-0.170	0.746	-0.314	0.890	Tie	Tie
2, 3, 6	-0.164	0.595	-0.283	0.714	Tie	Tie
2, 3, 7	-1.385	-0.012	-1.601	0.204	HEU	Tie
2, 5, 1	0.066	0.188	0.047	0.208	OPT	OPT
3, 1, 1	-0.284	0.186	-0.357	0.259	Tie	Tie
3, 1, 2	-0.435	0.438	-0.572	0.575	Tie	Tie
3, 1, 3	-0.497	0.355	-0.631	0.489	Tie	Tie
3, 1, 4	-0.152	0.084	-0.189	0.121	Tie	Tie
3, 1, 5	-0.865	0.080	-1.013	0.228	Tie	Tie
3, 3, 1	-0.336	0.525	-0.471	0.660	Tie	Tie
3, 3, 2	-1.960	-0.456	-2.197	-0.219	HEU	HEU
3, 5, 1	0.151	0.570	0.085	0.635	OPT	OPT
3, 5, 2	-0.263	-0.113	-0.286	-0.090	HEU	HEU
3, 5, 3	-0.072	0.046	-0.090	0.065	Tie	Tie
4, 1, 1	-0.234	0.863	-0.406	1.036	Tie	Tie
4, 1, 2	0.253	0.526	0.210	0.569	OPT	OPT
4, 1, 3	-0.589	0.278	-0.725	0.415	Tie	Tie
4, 2, 1	1.006	1.375	0.948	1.432	OPT	OPT
4, 2, 2	-0.288	0.134	-0.354	0.200	Tie	Tie
4, 3, 1	0.199	0.484	0.154	0.529	OPT	OPT
4, 5, 1	-0.162	0.072	-0.199	0.108	Tie	Tie
4, 5, 2	-0.051	0.074	-0.071	0.094	Tie	Tie
4, 5, 3	-0.096	0.082	-0.125	0.110	Tie	Tie
4, 5, 4	-0.112	0.083	-0.142	0.114	Tie	Tie

Table 5.8. Confidence Intervals for means of HEU-OPT with five and six new in-coming patients

# Patients, Shift, Instance	HEU-OPT 95% CI		HEU-OPT 99% CI		Winning Policy 95% CI	Winning Policy 99% CI
5, 2, 1	-0.537	0.510	-0.701	0.674	Tie	Tie
5, 2, 2	-0.128	0.166	-0.175	0.213	Tie	Tie
5, 2, 3	-0.005	0.390	-0.067	0.452	Tie	Tie
5, 2, 4	-0.079	0.905	-0.233	1.059	Tie	Tie
5, 4, 1	-0.087	0.007	-0.102	0.022	Tie	Tie
5, 4, 2	0.003	0.085	-0.010	0.097	OPT	Tie
5, 4, 3	0.008	0.098	-0.006	0.113	OPT	Tie
5, 4, 4	0.042	0.156	0.024	0.174	OPT	OPT
5, 4, 5	-0.046	0.061	-0.063	0.078	Tie	Tie
5, 5, 1	-0.165	0.006	-0.192	0.033	Tie	Tie
6, 2, 1	-0.095	0.130	-0.130	0.165	Tie	Tie
6, 2, 2	0.155	0.977	0.026	1.106	OPT	OPT
6, 2, 3	-0.422	0.550	-0.575	0.703	Tie	Tie
6, 2, 4	-0.269	0.127	-0.331	0.189	Tie	Tie
6, 4, 1	0.012	0.101	-0.002	0.114	OPT	Tie
6, 4, 2	0.028	0.256	-0.008	0.292	OPT	Tie
6, 4, 3	0.489	0.596	0.472	0.613	OPT	OPT
6, 4, 4	-0.158	-0.016	-0.181	0.007	HEU	Tie
6, 4, 5	0.202	0.389	0.172	0.419	OPT	OPT
6, 5, 1	-0.057	0.093	-0.081	0.117	Tie	Tie



(a) (b) (c) (d)

Figure 5.3. Boxplots of OPT policy wins - (a) # Patients: 2, Shift: 1, Instance: 2, (b) # Patients: 2, Shift: 3, Instance: 1, (c) # Patients: 2, Shift: 3, Instance: 3, and (d) # Patients: 2, Shift: 3, Instance: 4.

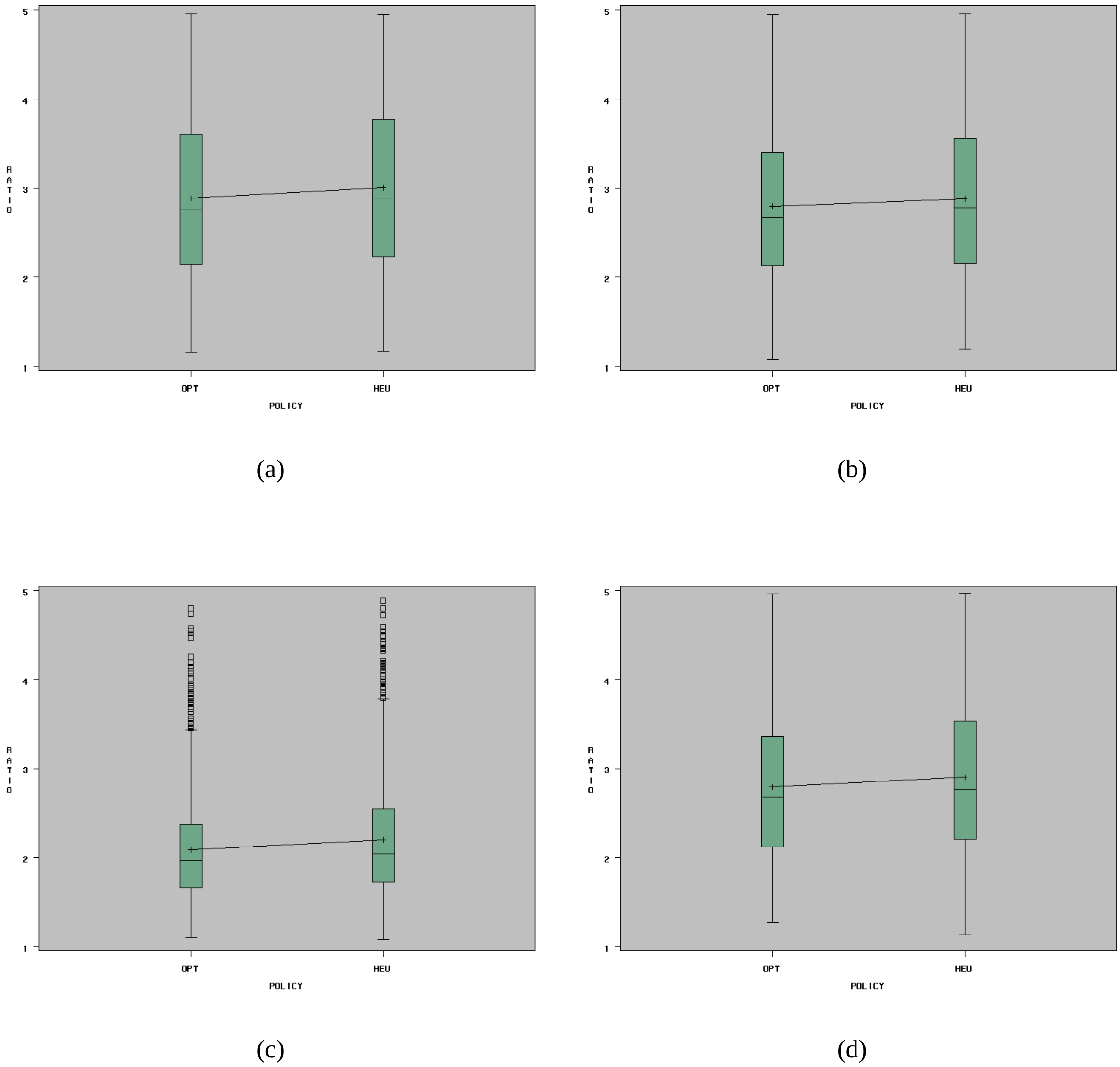
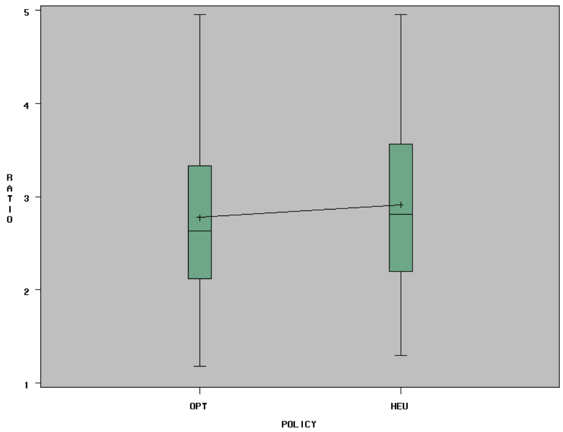
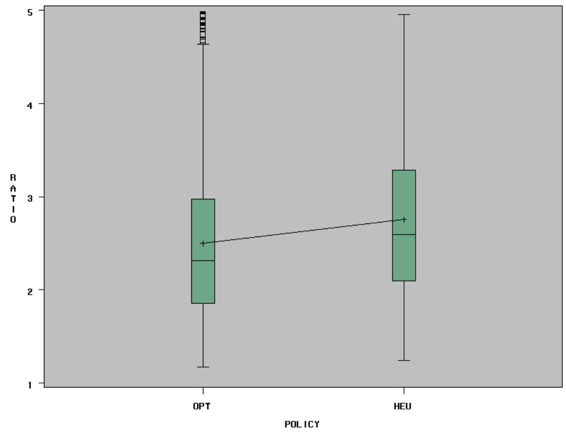


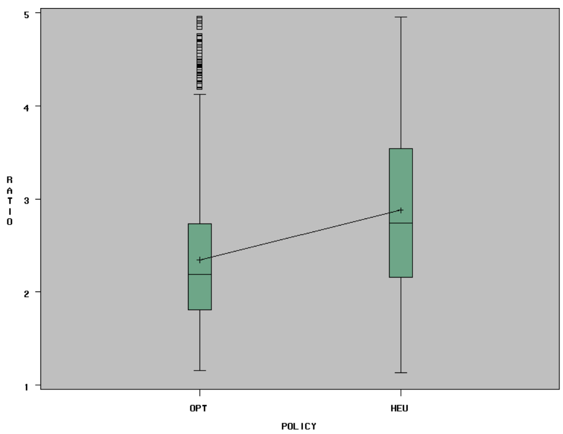
Figure 5.4. Boxplots of OPT policy wins - (a) # Patients: 2, Shift: 3, Instance: 5, and (b) # Patients: 2, Shift: 3, Instance: 6, (c) # Patients: 2, Shift: 5, Instance: 1, and (d) # Patients: 3, Shift: 5, Instance: 1.



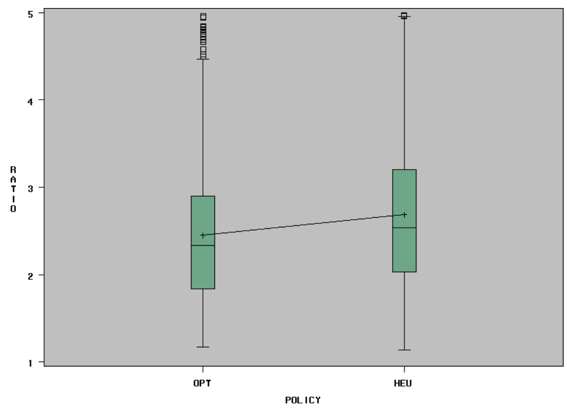
(a)



(b)

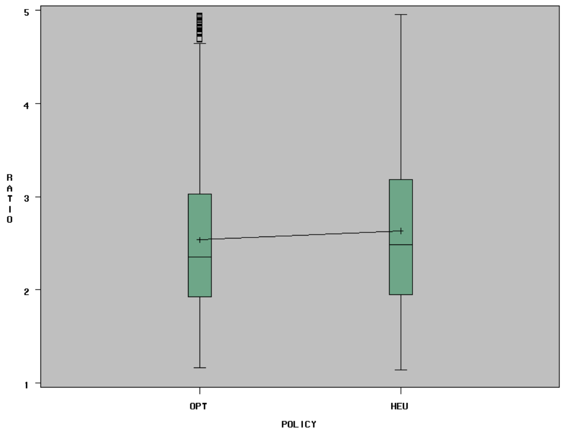


(c)

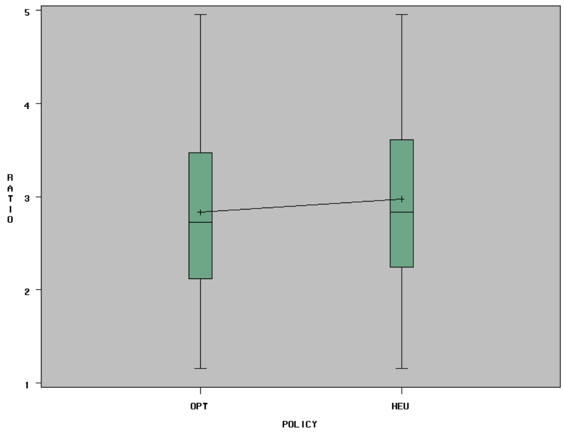


(d)

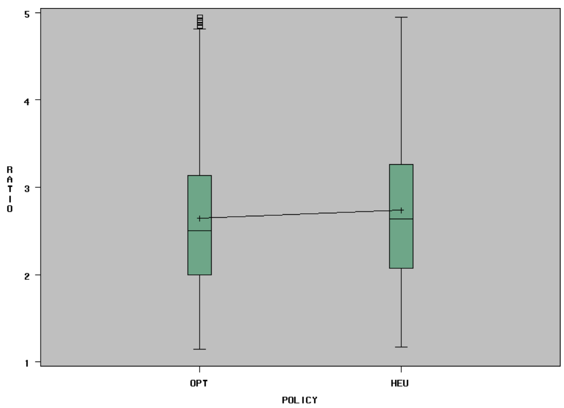
Figure 5.5. Boxplots of OPT policy wins - (a) # Patients: 4, Shift: 1, Instance: 1, (b) # Patients: 4, Shift: 1, Instance: 2, (c) # Patients: 4, Shift: 2, Instance: 1, and (d) # Patients: 4, Shift: 3, Instance: 1.



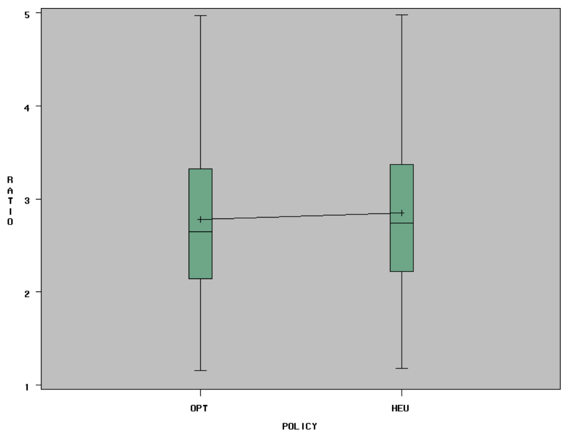
(a)



(b)

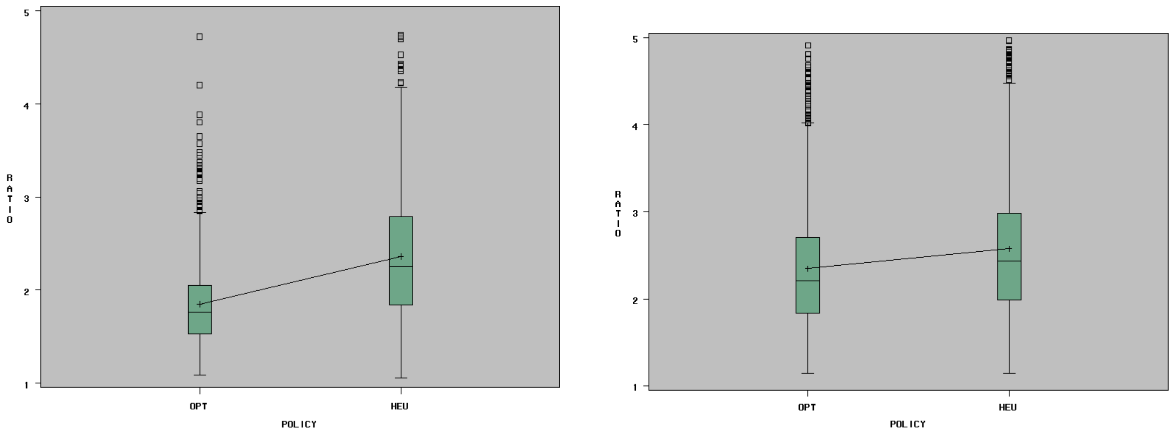


(c)



(d)

Figure 5.6. Boxplots of OPT policy wins - (a) # Patients: 5, Shift: 2, Instance: 3, (b) # Patients: 5, Shift: 2, Instance: 4, (c) # Patients: 6, Shift: 2, Instance: 2, and (d) # Patients: 6, Shift: 4, Instance: 2.



(a) (b)

Figure 5.7. Boxplots of OPT policy wins - (a) # Patients: 6, Shift: 4, Instance: 3 and (b) # Patients: 6, Shift: 4, Instance: 5.

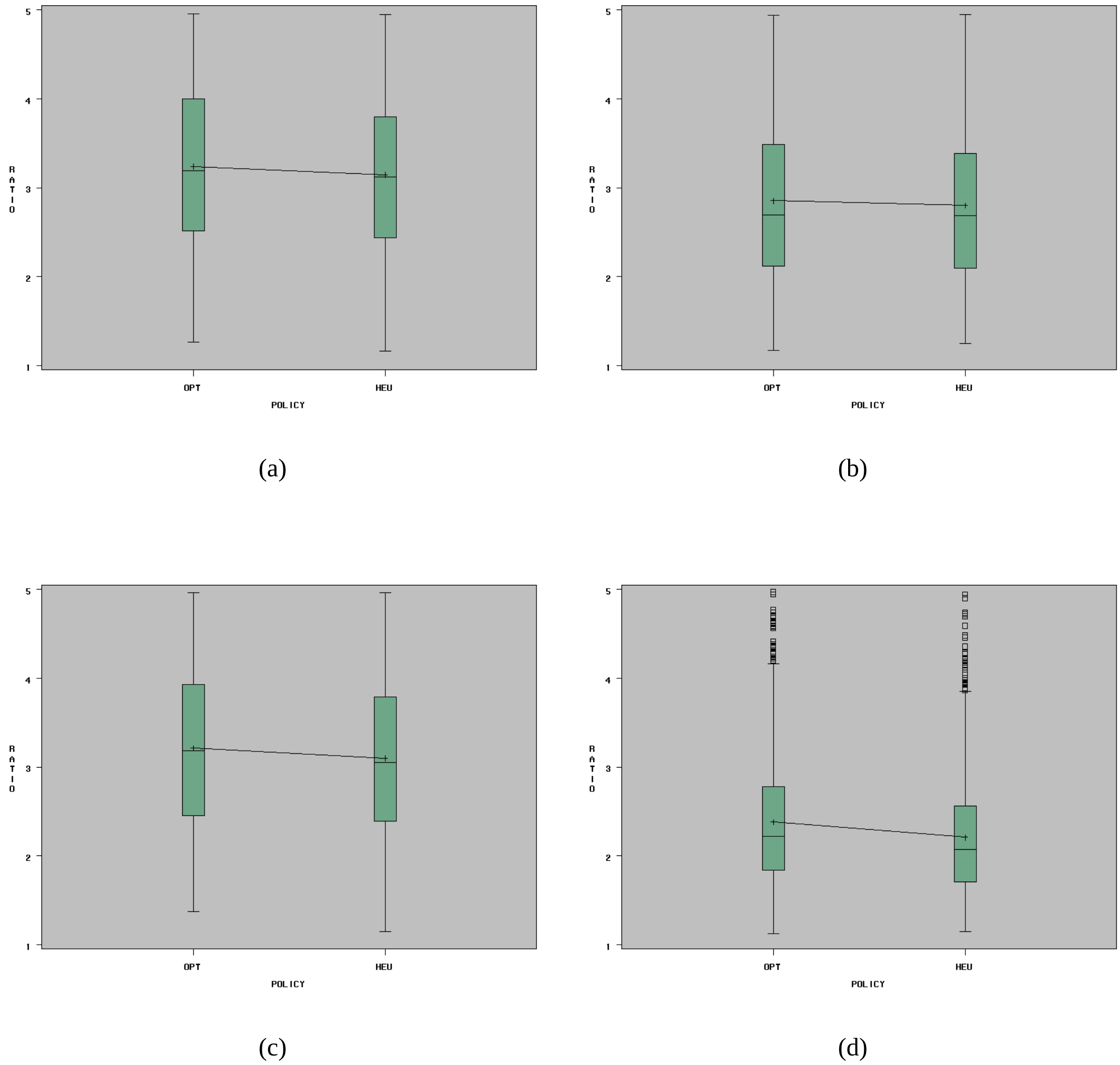


Figure 5.8. Boxplots of HEU policy wins - (a) # Patients: 2, Shift: 3, Instance: 7, (b) # Patients: 3, Shift: 1, Instance: 5, (c) # Patients: 3, Shift: 3, Instance: 2, and (d) # Patients: 3, Shift: 5, Instance: 2.

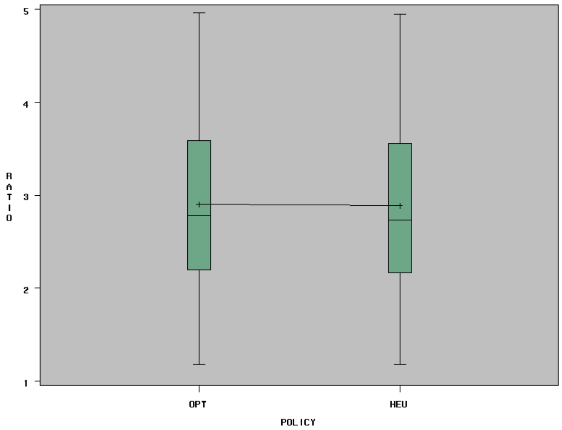
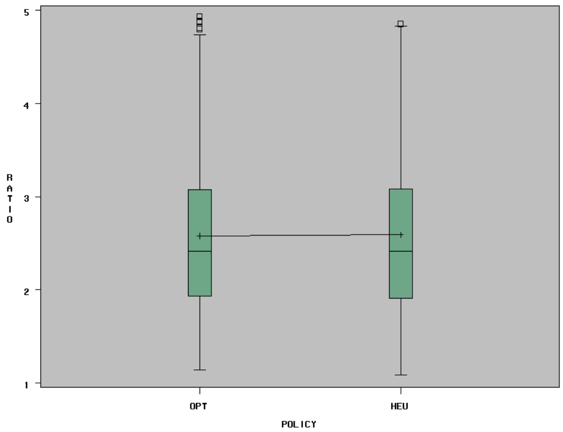
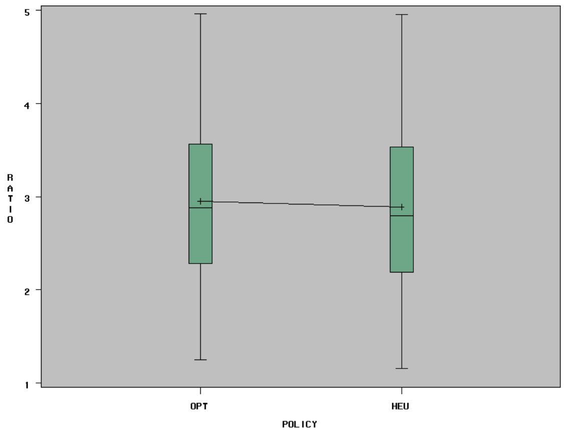


Figure 5.9. Boxplot of HEU policy wins - # Patients: 4, Shift: 1, Instance: 3.



(a)



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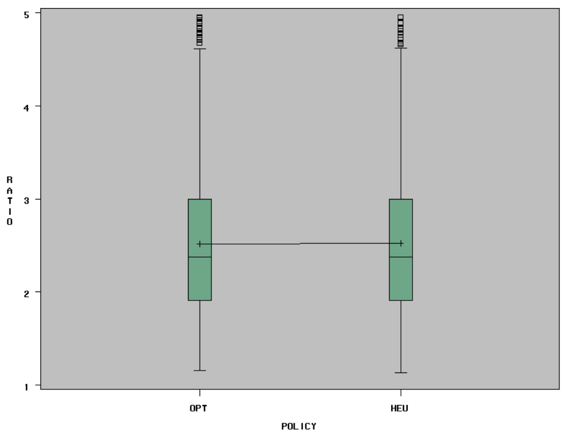

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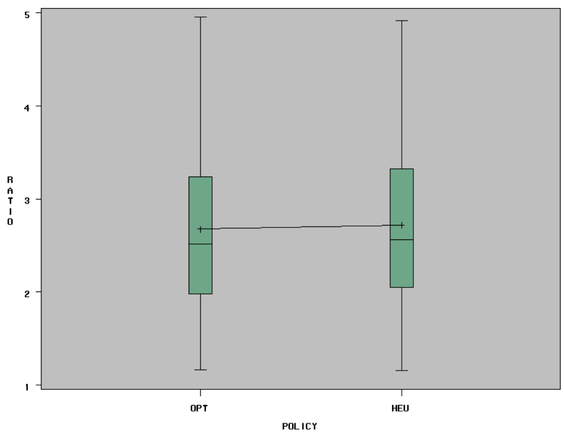
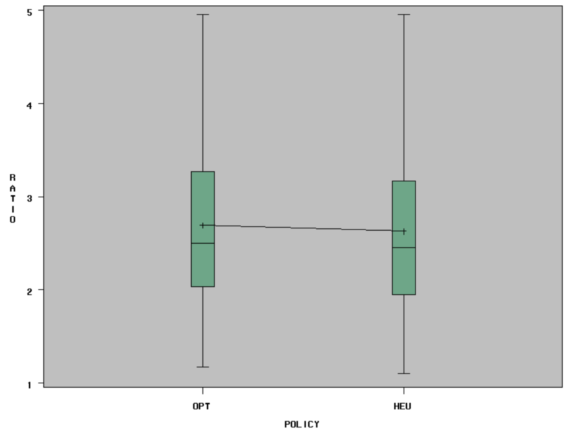
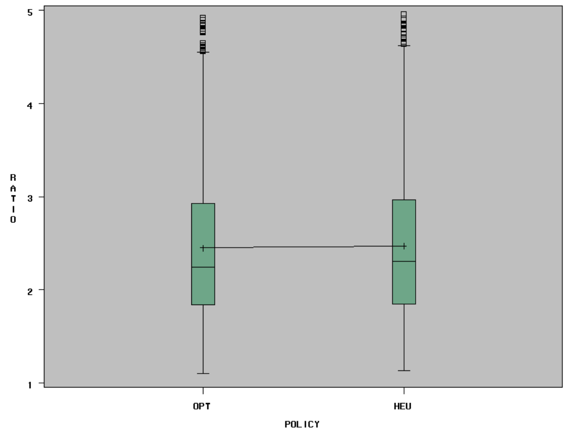


(d)

Figure 5.10. Boxplots for tie between OPT and HEU - (a) # Patients: 2, Shift: 1, Instance: 1, (b) # Patients: 2, Shift: 3, Instance: 2, (c) # Patients: 3, Shift: 1, Instance: 1, and (d) # Patients: 3, Shift: 1, Instance: 2.



(a)



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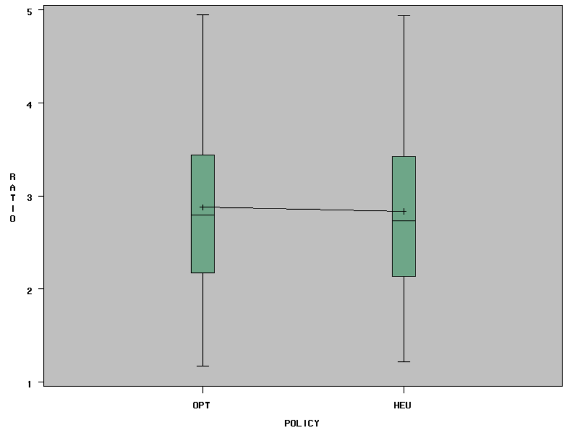
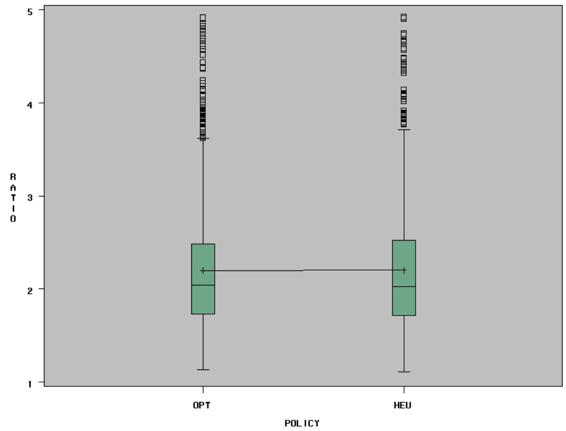
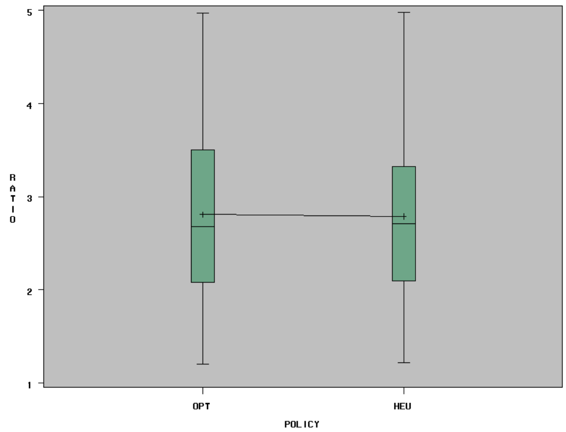


(c)

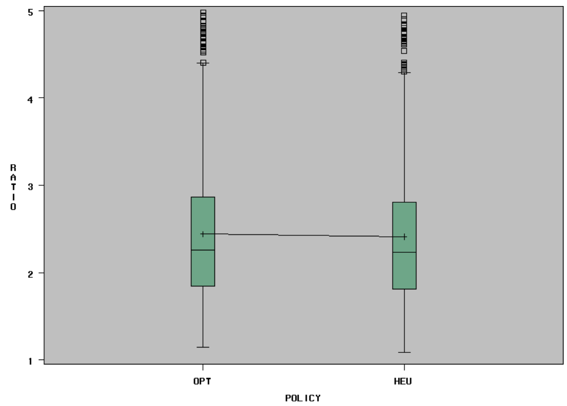


(d)

Figure 5.11. Boxplots for tie between OPT and HEU - (a) # Patients: 3, Shift: 1, Instance: 3, (b) # Patients: 3, Shift: 1, Instance: 4, (c) # Patients: 3, Shift: 3, Instance: 1, and (d) # Patients: 3, Shift: 5, Instance: 3.



(a)



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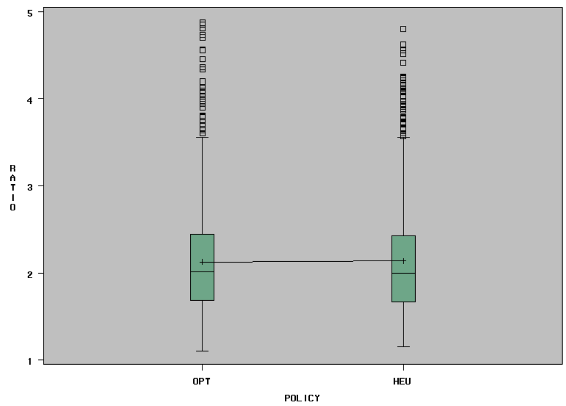
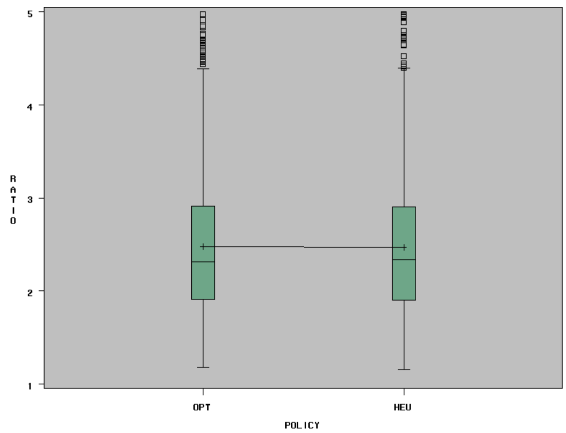
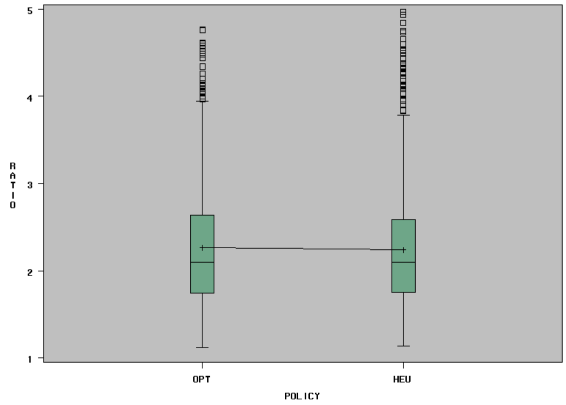


(c)

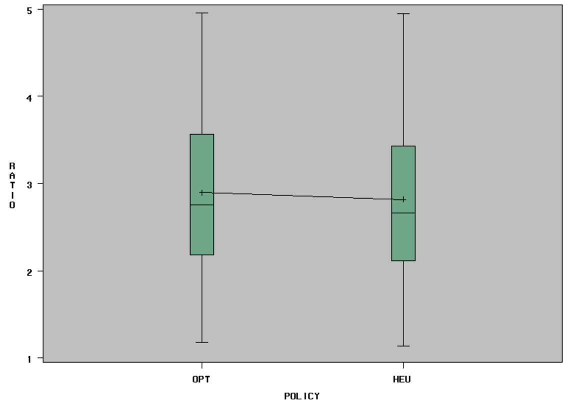


(d)

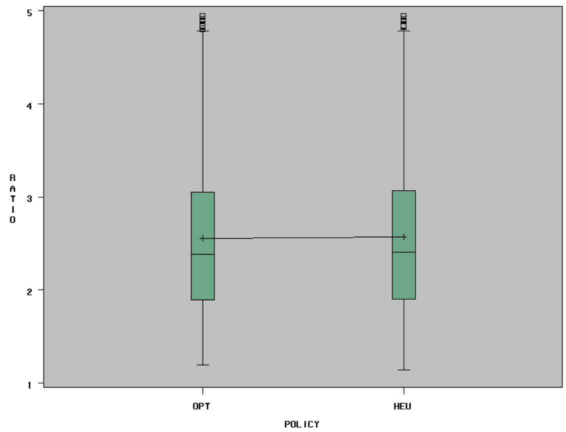
Figure 5.12. Boxplots for tie between OPT and HEU - (a) # Patients: 4, Shift: 2, Instance: 2, (b) # Patients: 4, Shift: 5, Instance: 1, (c) # Patients: 4, Shift: 5, Instance: 2, and (d) # Patients: 4, Shift: 5, Instance: 3.



(a)



(b)



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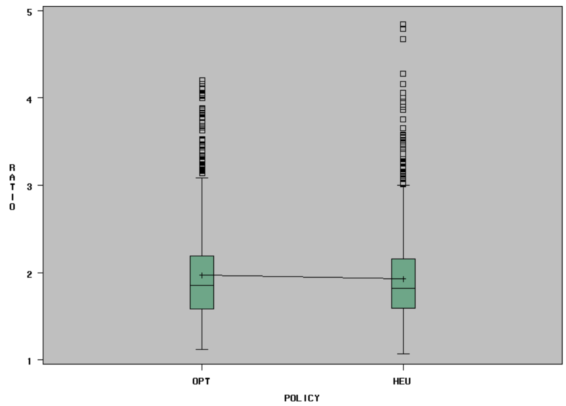


(d)

Figure 5.13. Boxplots for tie between OPT and HEU - (a) # Patients: 4, Shift: 5, Instance: 4, (b) # Patients: 5, Shift: 2, Instance: 1, (c) # Patients: 5, Shift: 2, Instance: 2, and (d) # Patients: 5, Shift: 4, Instance: 1.

5.3 Conclusion

Three major contributions were made in this dissertation:

- This research introduced a novel approach to the simulation community for constructing efficient simulation models based on data mining. This way of simulation modeling avoids misrepresentation of system dynamics and characteristics because it is entirely based on the pattern learned from a real data set collected from the system over a long period of time. Moreover, this approach reduces simulation states and is consequently more efficient to run. It should be also noted that data collection enabled by RFID technology makes this approach viable for many applications.
- This research introduced a tool to evaluate nurse-to-patient assignments and enable decisions in real time. Prior to a shift, the decision to hire agency nurses is determined by nurse supervisors, who assess whether the set of scheduled nurses is sufficient for that shift. The SIMNA model can aid them in their decisions by providing a tool to test nurse-to-patient assignments.
- This research introduced the OPT policy to solve for assignment of new admissions during a shift. Traditionally, a nurse who has the least number of patients or who had the least workload until the instance of arrival - like in the HEU policy - would get the newly-admitted patient. HEU policy could worsen the imbalance as future workload is totally ignored. The OPT policy, considering the past as well as approximating the future, is likely to reduce the imbalance.

It should be noted that all the simulations, written in C++, were run on a Dual 2.4-GHz Intel Xeon Workstation. It took less than three minutes to run one thousand scenarios to obtain the results discussed in sections 4.2 and 5.2.1. Henceforth, it is possible to use these tools in real time to make nurse-patient assignment decisions.

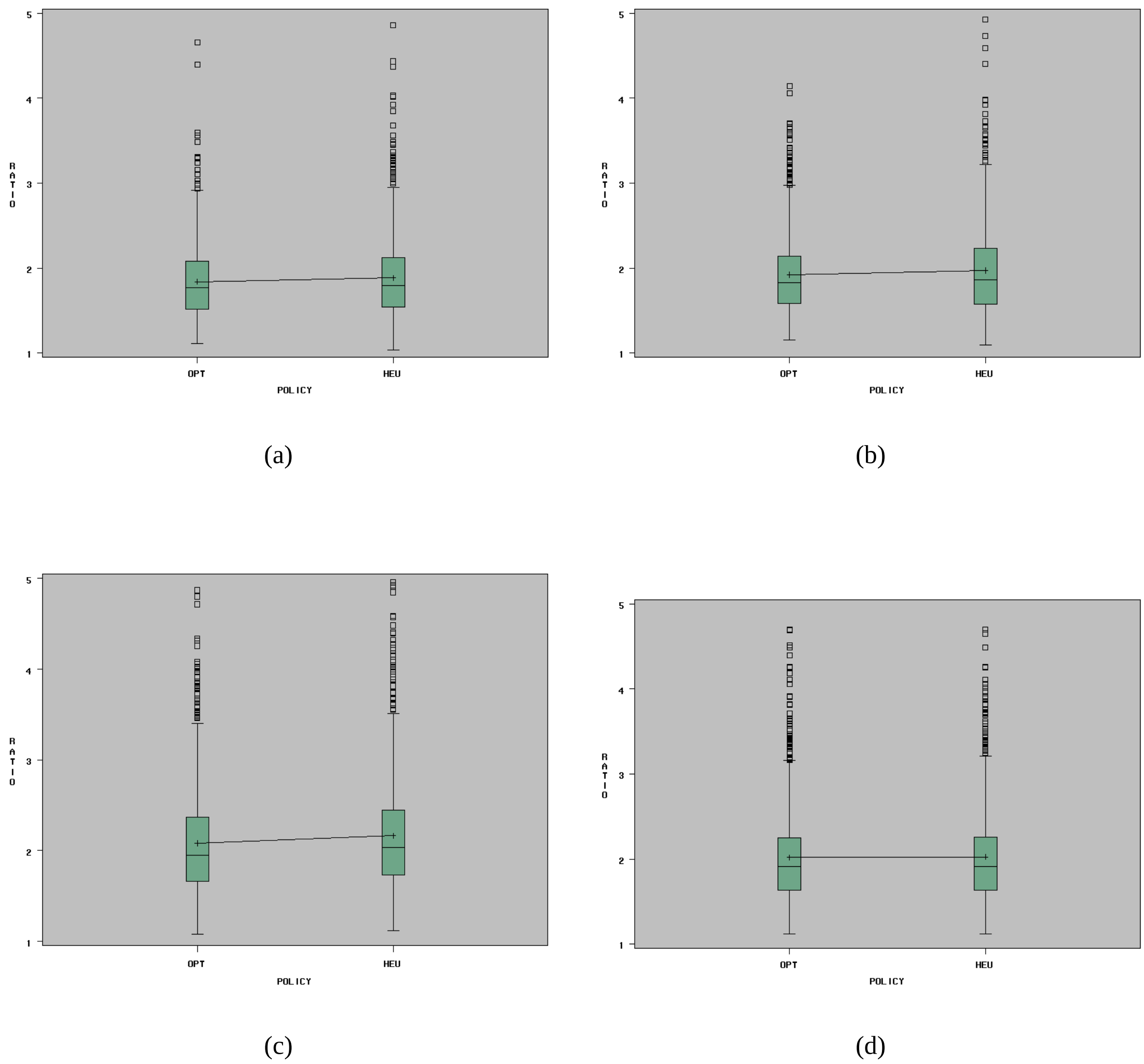
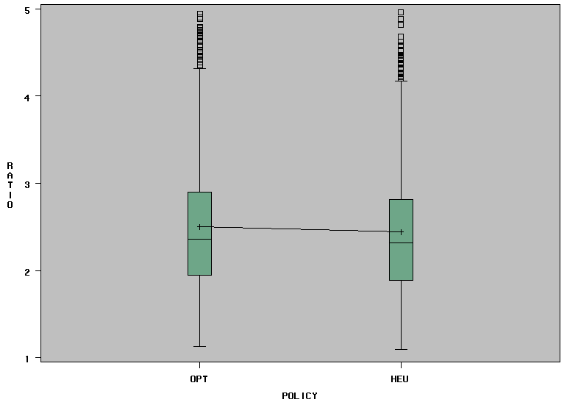
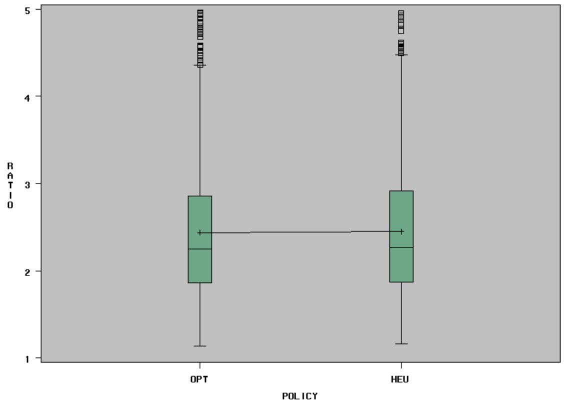


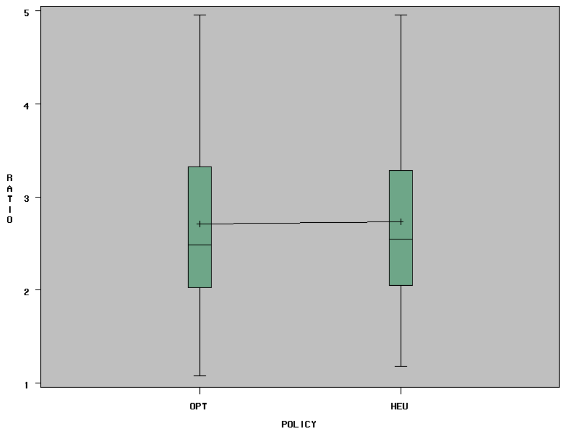
Figure 5.14. Boxplots for tie between OPT and HEU - (a) # Patients: 5, Shift: 4, Instance: 2, (b) # Patients: 5, Shift: 4, Instance: 3, (c) # Patients: 5, Shift: 4, Instance: 4, and (d) # Patients: 5, Shift: 4, Instance: 5.



(a)



(b)



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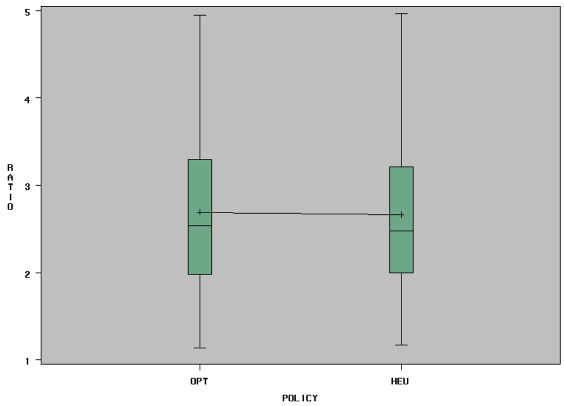
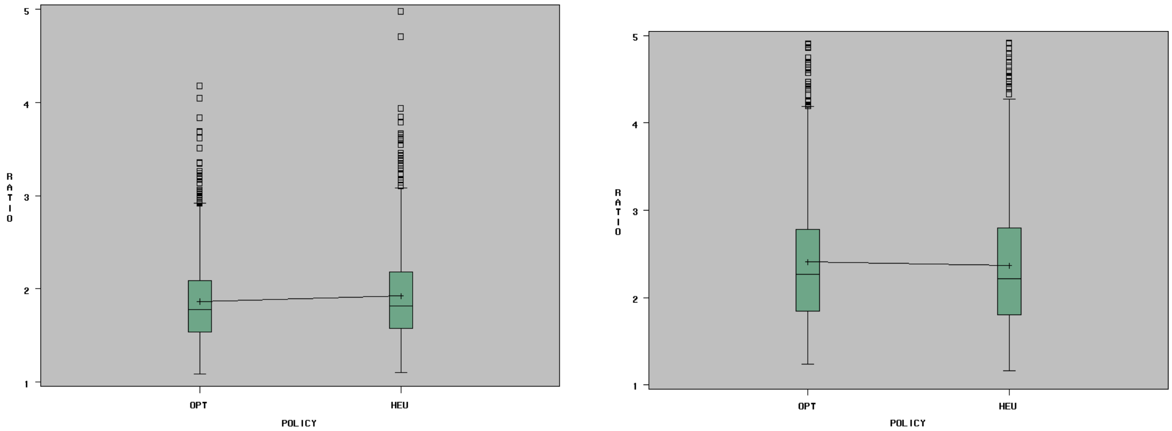


(d)

Figure 5.15. Boxplots for tie between OPT and HEU - (a) # Patients: 5, Shift: 5, Instance: 1, (b) # Patients: 6, Shift: 2, Instance: 1, (c) # Patients: 6, Shift: 2, Instance: 3, and (d) # Patients: 6, Shift: 2, Instance: 4.



(a) (b)

Figure 5.16. Boxplots for tie between OPT and HEU - (a) # Patients: 6, Shift: 4, Instance: 1 and (b) # Patients: 6, Shift: 4, Instance: 4.

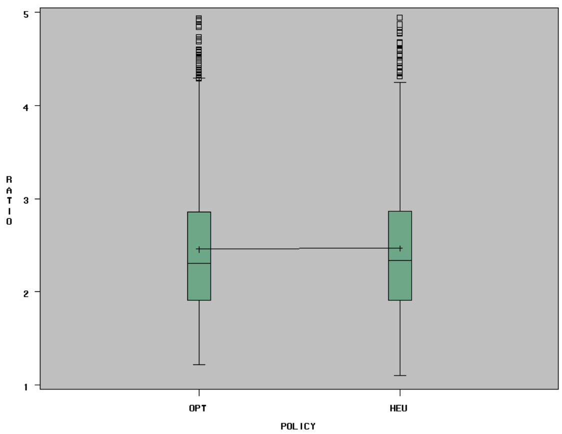


Figure 5.17. Boxplot for tie between OPT and HEU - # Patients: 6, Shift: 5, Instance: 1.

CHAPTER 6

FUTURE WORK

This dissertation work has laid a foundation for nurse-patient assignment research. It has introduced a tool to evaluate different policies of nurse-patient assignments. It has also introduced the OPT policy to aid assignments for new patient admissions. The following are the other promising elements that can be incorporated to this research.

1. Online Updating: The data used in this research was collected from March to September of 2004. In this approach, capturing an evolving dynamics of a system in simulation is only possible by constantly appending new data and rebuilding the trees. In a system like Baylor, where data is collected continuously, it is possible to link CART and SIMNA to the database to update itself to reflect the evolving dynamics of the system. Such dynamically updating simulations are likely to represent the reality immediately and provide better results than the simulations built from stationary data.
2. Data Mining Techniques: In the SIMNA model presented in this dissertation, CART was utilized as the data mining technique to model the pattern of dynamics present in the system. Incorporating newer tree models, such as, bagged trees and boosted trees would be an interesting topic for future research. Friedman et al. [35] and Friedman [34] presented such a version of boosted trees called multiple additive regression trees (MART). Similar to CART® software, Salford System also has TREENET/MART® software (www.salfordsystems.com) that could provide MART trees. Other popular data mining methods, such as, Linear Discriminant Analysis, Logistic Regression, Separating Hyperplanes, Neural Networks, and Support Vector Machines have tremendous success in modeling many application. Comparing simulation models built with these

data mining techniques for their accuracy to represent the real system is another interesting research path possible from this dissertation.

3. Alternate Assignment Policy: It was found from this research that OPT and HEU won eighteen and five times, respectively. Intuitively, HEU's solution should get better towards the end of a shift as workload imbalance information from the past is naturally more important at the end. Similarly, assuming OPT approximates the future accurately, it should perform relatively better than HEU at the beginning of a shift. Identifying circumstances suitable for OPT and HEU is another interesting area of research. Perhaps, a policy to use OPT for first half and HEU for the second half of the shift would be interesting to consider. Results from this policy, which can be named as the OPTHEU policy, would shed light on determining characteristics that affect OPT and HEU policies.
4. "Time Period-Action Q-Factors" method: In this research, a brief discussion about the potential for Q-Factors methods was given especially in circumstances when a simulator is available. However, the existing algorithms of Q-Factors method will not work for the nurse-patient assignment problem as the number of state-action pairs are huge. It will be interesting to explore the possibility of having Q-Factors for arrival-action pairs instead of state-action pairs. This approach will reduce the number of Q-Factors significantly. It should to be noted that with stochastic arrivals, it is still difficult to update all the arrival-action pairs accurately within reasonable number of simulation runs. For example, the first arrival in a simulation run is likely to be significantly different from another first arrival simulated in a different simulation run. To tackle this issue, the shift can be divided into smaller time periods to get Q-Factors for each period-action pairs. The actions in this research are to assign the newly-admitted patient to a nurse. There is no action required in a time period if there is no new admits. Therefore, with the "Time Period-Action Q-Factors", the number of Q-Factors would be equal to the number of periods times the number of nurses. For example, for an eight hour shift broken into one

hour periods with five nurses working, there would be just forty Q-Factors. As mentioned earlier, it would take just three minutes to run one thousand scenarios, and it is possible to update the Q-Factors for real time decision making at Baylor in the proposed "Time Period-Action Q-Factors" method.

5. Optimization: Exploring the applicability of simulation-optimization methods, such as [6], and [36], is also an interesting topic for future research. The traditional simulation-optimization methods, in general, use some kind of approximated value for the gradient of the simulation. The static structure of the data-integrated simulation introduced in this dissertation is clearly modeled by the CART. Extracting the gradient of simulation from CART and using it for optimization is potentially feasible and worth exploring.
6. Patient Discharge: For simplicity in modeling, it was assumed that there are no patient discharges during a shift. However, it is common to have discharges during a given shift. An estimated discharge rates for different shifts are given in table 6.1. Incorporating patient discharges in SIMNA, and hence in OPT and HEU policies, is another interesting possible extension of this research.

Table 6.1. Patient Discharge Rate

6am to 9am	**9am to Noon**	**Noon to 3pm**	**3pm to Midnight**	**Midnight to 6am**
1%	70%	25%	3%	1%

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BIOGRAPHICAL STATEMENT

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